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The Effects of Carry-on Baggage on Aircraft Evacuation Efficiency

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Abstract

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The most frequent obstacle of an aircraft evacuation is the passengers carrying baggage while evacuating. Passengers who insist on taking their carry-on baggage during an emergency evacuation not only slow down the evacuation process but also act as a significant risk to the safety of other passengers. This study investigated the factors that affect passengers' behavioral intention to evacuate with carry-on baggage and the effects of evacuating with carry-on baggage on the total evacuation time. Overall, two studies were conducted to provide an outline of the factors that affect and affected by carry-on baggage.

Study 1 used an agent-based model, AnyLogic, to simulate the aircraft evacuation model of an A380. The model was validated, and a two-way Analysis of Variance (ANOVA) was conducted to examine the effects of the percentage of passengers evacuating with carry-on baggage and exit selection choices on the total evacuation time. The simulation results suggested that the mean evacuation time for 0% was significantly lower than 50% and 80%. The mean evacuation time for the shortest queue choice was also lower than the closest exit choice.

Study 2 used an expanded theory of planned behavior (TPB) to determine the factors that affect passengers' intentions to evacuate with carry-on baggage. The total sample size was 281 after data cleaning. The confirmatory factor analysis (CFA) and structural equation model (SEM) were used to analyze the data. The results indicated that attitude was the significant determinant of passengers' intention to evacuate with carry-on baggage. The factor of 'perceived risk' was not supported, but the results showed that the opposite effect of the hypothesis was significant.

The results of this study fill a gap in the research regarding passengers' behavior of evacuating with carry-on baggage. Potential applications of this study will also help the federal regulations, airlines, and aircraft manufacturers by providing a better understanding of carry-on baggage at aircraft emergency.

Dedication

This thesis is dedicated to my beloved parents, who continually provided moral, emotional, and financial support.

To my sister, best friend, and my joy of life, Su-Ah Lee.

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Chapter I: Introduction

The efficiency of an aircraft emergency response is critical as it is closely connected to the survivability of the people on board and even potentially life-threatening. According to the Federal Aviation Administration (FAA, 2004), all passengers, including crewmembers at full seating capacity, should evacuate within 90 seconds or less under the emergent situation. This 90-second rule is crucial for the airlines to ensure passengers have the ability to survive an aircraft accident and minimize the damage to the aircraft. However, it is extremely challenging to meet the regulation as the evacuation time is affected by many factors. The factors include human factors such as passengers' panic behavior and startle effect, as well as the number of emergency exits available, the flight crew training, and passengers' behavior to bring their carry-on baggage while evacuating. Any delay from the evacuation process could reduce the survivability of the passengers.

People tend to take their baggage while evacuating from an aircraft for different reasons. For instance, panic behavior could impair the decision-making process (Wang et al., 2015), or the passengers might not be aware of the consequences of taking baggage with them (Prew, 2017). Passengers who insist on taking their carry-on baggage at emergency evacuations not only slow down the evacuation process but also act as a significant risk to the safety of other passengers (National Transportation Safety Board [NTSB], 2000). Passengers opening their overhead baggage compartment doors during an emergency could allow carry-on baggage to fall into the cabin and act as an obstacle (Transportation Safety Board of Canada [TSB], 2007). Passengers standing in the aisle to get their baggage also act as an obstacle for passengers behind. Moreover, the emergency slides can be damaged from the baggage attachments, such as the buckles.

Retrieval of carry-on baggage during an emergency has been an ongoing problem as early as 1981. The NTSB report on Allegheny Airlines Douglas DC-9 mentioned the problem of carry-on baggage that the passengers encountered baggage in the aisle as some passengers tried to retrieve their baggage during evacuation (NTSB, 1981, as cited in Flight Safety Foundation, 1997).

Inappropriate exit selection choices, in addition to the evacuation with baggage, could further delay the overall evacuation process. Exit selection choices are the methods that the passengers choose their exits. The *closest exit selection* refers to the situation where the passengers choose the closest exit from their seats to evacuate. In terms of the *shortest queue selection,* passengers will be assigned to the exit with the shortest queue. The optimum exit selection choice may vary depending on the number of passengers carrying baggage during evacuation. The goal of this study was to examine the effects of exit selection choice and the number of passengers evacuating with carry-on bags on overall evacuation efficiency.

Statement of the Problem

The NTSB (2000) surveyed 457 passengers from aircraft evacuations and reported that nearly 50% of passengers with carry-on bags on-board admitted that they tried to take their bags during the aircraft evacuation, and most passengers actually exited with their bags. Survey responses from 36 cabin crews also showed that the biggest impediment to an expeditious evacuation was the passengers evacuating with carry-on baggage (NTSB, 2000). Research supported that carry-on baggage can be the main factor that delays the evacuation process. According to Chang and Yang (2011), survivors of the crash of China Airlines CI-120 in 2007 supported that carry-on baggage acted as obstacles and created a barrier near the exits as the passengers dropped them.

Numerous studies have been conducted to study the efficiency of aircraft emergency evacuation without considering delay due to baggage (Deng, 2016; Miyoshi et al., 2012; Zhi-ming et al., 2014). Similarly, the effect of the exit selection choice was studied by researchers, but the baggage was not considered (Liu & Deng, 2020; Togher et al., 2009). In addition, few studies considered the effect of baggage during the aircraft boarding process (Tang et al., 2018) and passenger trains (Capote et al., 2012). Presently, no study has concurrently investigated the effects of baggage and exit selection choice on aircraft evacuation efficiency.

Significance of the Study

A significant amount of delay in an emergency evacuation can cost human lives. In fact, the most frequent obstacle of an aircraft evacuation is the passengers carrying baggage while evacuating (Cosper & Mclean, 2004). For instance, passengers' evacuating behavior with carry-on baggage was observed in the recent accident of Aeroflot Flight 1492, which led to 41 fatalities (Airlines Travel, 2020; Interstate Aviation Committee [IAC], 2019). Video taken during the accident of American Airlines Flight 383 also showed passengers evacuating with carry-on bags even though the cabin crew instructed them to drop their bags (Chicago Sun-Times, 2017). The NTSB Chairman Robert Sumwalt also made stern comments about the evacuation process of American Flight 383 (Babwin, 2018). The NTSB also called on passengers who slowed down the evacuation process by ignoring the flight attendants' instructions to leave their baggage.

Passengers' behavior of evacuating with carry-on baggage in recent aircraft accidents showed that the mitigative actions were not effective (NTSB, 2019).

Due to the accidents, the NTSB (2000) recommended the FAA to address problems regarding carry-on baggage during evacuations. Congruently, FAA advisory circular AC121-24C stated that the safety briefing cards in the aircraft should provide information that passengers should not take their luggage to the exit in the event of an emergency (FAA, 2003). However, a disturbing fact was that passengers were not aware of the importance of carry-on baggage restrictions at aircraft evacuations (Chang & Yang, 2011). In 2018, the NTSB further recommended that the FAA should perform studies to "measure and evaluate the effects of carry-on baggage on passenger deplaning times and safety during an emergency evacuation" (p. 66). Therefore, this study responded to the recurring question of the impact of carry-on bags on evacuation efficiency and safety. It is also essential to understand the root of the problem in order to solve the problem. To understand the passengers' behavioral intention of retrieving carry-on baggage, Structural Equation Modeling (SEM) analysis and Theory of Planned Behavior (TPB) were used.

Purpose Statement

The purpose of this study was to investigate the effect of passengers' evacuating with carry-on baggage on passenger evacuation efficiency using different exit selection choices and the behavioral intention of the passengers evacuating with carry-on baggage. In other words, the purpose of this study was to examine the relationship between the number of passengers evacuating with their carry-on baggage and exit selection choice with passenger deplaning time during an emergency evacuation. A further goal was to evaluate the passengers' behavioral intentions and mental models regarding the carry-on baggage using the SEM of the survey data.

Research Question and Hypotheses

There were two studies in this paper. Study 1 used simulation software and Study 2 used a survey. Simulation software was not capable of investigating the passengers' behavioral intention of retrieval of carry-on baggage. Therefore, Study 2 was conducted in addition to Study 1 to give an insight into the overall evacuation process.

Study 1 RQ

Study 1 investigated the following research questions. Dependent variable (DV), evacuation efficiency was measured as passenger deplaning time. Two independent variables were the percentage of passengers evacuating with carry-on baggage and exit selection choice. The percentage was categorized into three levels: 0%, 50%, and 80%, and the exit selection choice was divided into two levels: the shortest-queue selection and the closest exit selection.

1. What is the effect of the percentage of passengers evacuating with carry-on baggage (IV) on the passenger deplaning time (DV)?
2. What is the effect of exit selection choice (IV) on passenger deplaning time (DV)?
3. What is the effect of the interaction between the percentage of passengers evacuating with carry-on baggage (IV) and exit selection choice (IV) on passenger deplaning time (DV)?

Study 1 H_0

$H_0$1: There is no significant effect of the percentage of passengers evacuating with carry-on baggage (IV) on the passenger deplaning time (DV).

$H_0$2: There is no significant effect of exit selection choice (IV) on the passenger deplaning time (DV).

$H_0$3: There is no significant interaction between the percentage of passengers evacuating with carry-on baggage (IV) and the exit selection choice (IV) on the passenger deplaning time (DV).

Study 2 RQ

Study 2 involved an online survey to ascertain passengers' awareness, behavioral intention, and personal attitude regarding evacuation with carry-on baggage. The research question utilized TPB to determine the attitudes, perceived value of tangible and intangible products in the luggage, perceived value of risk, and awareness towards passengers' intention to evacuate with carry-on baggage.

1. Does attitude significantly affect the behavioral intention of evacuating with carry-on baggage?
2. Does perceived risk significantly affect the behavioral intention of evacuating with carry-on baggage?
3. Does perceived value of tangible products in the luggage significantly affect the behavioral intention of evacuating with carry-on baggage?
4. Does perceived value of intangible products in the luggage significantly affect the behavioral intention of evacuating with carry-on baggage?
5. Does awareness significantly affect the behavioral intention of evacuating with carry-on baggage?

Study 2 Hypotheses

H4: Attitudes are positively related to passengers' intentions to evacuate with carry-on baggage.

H5: Perceived risk is negatively related to passengers' intention to evacuate with carry-on baggage.

H6: Perceived value of tangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H7: Perceived value of intangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H8: Awareness is negatively related to passengers' intention to evacuate with carry-on baggage.

Delimitations

For Study 1, it is challenging to gain data from real-world evacuation scenarios. Due to the conditions necessary for this study, an agent-based modeling software called 'Anylogic' was used. The study only simulated the evacuation process of the first floor of an Airbus A380.

Furthermore, this study cannot represent all aircraft evacuations. Aircraft evacuation can be caused by many reasons, including engine failure, fire, or even terrorist attacks. However, the emergency scenario for this study only addressed evacuation due to fire.

For Study 2, several delimitations defined the boundaries of the study. The study was delimited to use the TPB as a theoretical framework and SEM as the data analysis method. The study was also delimited to a non-probability convenience sampling method by using Amazon Mechanical Turk (MTurk). MTurk has been widely used by researchers to gather reliable data from a diversified pool of people (Rice et al., 2017).

Limitations and Assumptions

Model Limitations and Assumptions

Anylogic is software that involves simulation limits such as lack of replication of the human factors. Therefore, several passenger-related and aircraft-related assumptions were considered. First, passengers were not able to change the exit selection once allocated. Second, evacuation with children, group travel, or passengers with disability were not considered. The social force model was embedded as the default algorithm to simulate passengers' moving speed, which were based on compiled previous studies. However, the social force model did not consider panic behavior, emotion, situation awareness, and injury. Finally, the amount, weight, and size of the carry-on baggage were consistent for the passengers who evacuate with carry-on baggage.

Survey Limitations and Assumptions

Several limitations and assumptions exist for the current study. First, the survey was conducted online, so the participants were not randomly selected. Therefore, the results of this study may not be generalizable to a population outside of people who participated in MTurk. However, studies have found that MTurk holds promise than other online survey tools in terms of representativeness (Horton et al., 2011; Redmiles et al., 2019). Horton et al. (2011) supported that the validity of the surveys conducted on MTurk was as valid as other kinds of experiments while reducing time and cost to conduct the survey. Redmiles et al. (2019) supported that MTurk responses regarding security and privacy experiences were more representative of the United States population than responses from census-representative web-panels.

Second, the respondents might not interpret the questions the same way due to the self-administration of the online survey (Vogt et al., 2012). However, the effect of the limitation was minimized by confirming that the questions were unambiguous through a pilot study.

Third, it was assumed that the respondents responded truthfully to the survey. It is sensible to assume that the anonymity of the survey would allow more honest responses. Measures were taken to utilize appropriate incentives that promoted desired response behaviors. The informed consent of the survey also reminded the participants that the participation was totally voluntary and that they could discontinue the survey at any time without any consequences. The researcher was alerted for survey cheaters by looking at the completion time and any answer patterns such as straight-lining.

Finally, pre-determined criteria were not set to assure high-quality responses. MTurk allows researchers to filter potential participants based on a set of pre-determined criteria. For example, the ‘Masters’ requirement selects participants who are active MTurk users. However, Peer et al. (2014) supported that restricting the survey participants with ‘Masters’ qualification only could reduce the population size and thus, increase the time to receive the responses. Harms & Desimone (2015) further supported that ‘Masters’ requirement can cause problems such as sample non-independence. Therefore, pre-determined criteria were not set to filter participants.

Summary

Passengers evacuating with carry-on baggage has been an ongoing problem as they can act as an obstacle for other passengers and delay the evacuation process. As the evacuation efficiency is directly related to the survivability of the passengers, many studies were conducted to investigate the effective measures to optimize aircraft emergency evacuation. The NTSB also recommended conducting a study to determine the effects of carry-on baggage on evacuation efficiency. Still, no study has concurrently investigated the effects of carry-on baggage and exit selection choice on aircraft evacuation efficiency.

This paper included two studies. Study 1 used a simulation software called AnyLogic to investigate the effects of carry-on baggage and evacuation choice on evacuation efficiency. Study 2 surveyed participants to investigate the behavioral intention of the passengers evacuating with carry-on baggage. Overall, this study investigated the behavioral intention of the passengers evacuating with carry-on baggage, to what extent that behavior delays the overall evacuation process, and suggested the optimum evacuation choice when evacuating with carry-on baggage.

Chapter II reviewed the literature on different evacuation simulation models and the impact of different exit selection choices. Human behavior during an emergency and the theoretical framework, SEM analysis and TPB were also reviewed. Factors affecting the behavioral intention of passengers were analyzed by the TPB. Chapter III detailed the research population and sample, treatment of the data, and the ethical concerns for the survey part of the study. Model structure of aircraft evacuation and baseline model validation for the simulation were discussed in Chapter III.

Definitions of Terms

Agent-Based Model	Dynamic model that simulates how individuals interact with other individuals and space around them to make decisions (Bone, 2018)
Attitudes	The degree to which a passenger has a favorable or unfavorable opinion toward the behavior of evacuating with carry-on baggage (Ajzen, 2002a)
Awareness	Having a particular interest in or experience of the rules of passengers' evacuating with carry-on baggage (Bashir et al., 2019)
Behavioral Intention	An indication of how much a passenger is willing to evacuate with their carry-on baggage during an aircraft evacuation
Pedestrian Library	Simulation tool that helps researchers to model and evaluate how crowd movements behave in an environment and remove any potential inefficiencies (Anylogic, n.d.b)
Perceived Risk	Risk-as-feeling approaches by personalizing the risk associated with the immediate incident (Kinateder et al., 2015)
Perceived Value	Passengers' overall evaluation of the tangible and intangible products based on perceptions of what is in the carry-on baggage (Meng & Cui, 2020)

Social Force Model Continuous model that considers the interactions between pedestrians and other forces, so the movement of each pedestrian is regulated by Newtonian mechanics (Kang et al., 2019)

Theory of Planned Behavior A psychological theory used to explain and predict human behavior through the lens of behavioral intention (Ajzen, 2002a)

List of Acronyms

ABM	Agent-Based Model
AMOS	Analysis of Moment Structure
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
CA	Cellular Automaton
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Construct Reliability
DV	Dependent Variable
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
GFI	Goodness of Fit Index
IAC	Interstate Aviation Committee
IRB	Institutional Review Board
IV	Independent Variable

MSV	Minimum Shared Variance
MTurk	Amazon Mechanical Turk
NFI	Normed Fit Index
NTSB	National Transportation Safety Board
PBC	Perceived Behavioral Control
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SPSS	Statistical Package for Social Sciences
TPB	Theory of Planned Behavior
TSB	Transportation Safety Board of Canada

Chapter II: Review of the Relevant Literature

The purpose of this literature review was to identify the relevant literature and synthesize it to show the problem of interest, the gap in the research literature, and the importance of the study. The articles reviewed were related to the effects of carry-on baggage, exit selection choices, simulation and modeling, and human behavior at an aircraft emergency evacuation. Further, this study also analyzed the Structural Equation Modeling (SEM), the Theory of Planned Behavior (TPB), and the factors of the TPB for the survey part of the study. The review begins by summarizing previous studies using simulation. The review continues to discuss existing findings related to the effects of carry-on baggage and exit selection choices at an emergency. Overall, the review relates the theories to the proposed hypotheses.

Effects of Carry-on Baggage

Passengers are not allowed to bring their carry-on bags to the exit while evacuating from an aircraft (FAA, 2003). This is because passengers' behavior to retrieve their baggage can cause the baggage to fall into the cabin or act as an obstacle, and delay the evacuation time. Due to these reasons, research was strongly recommended to derive rules and regulations regarding the effects of carry-on baggage at emergency evacuation (NTSB, 2018).

Passengers evacuating with carry-on Passengers dropping carry-on baggage can create an obstacle and block the evacuation route for rear passengers. More problems occur when passengers carry their bags to the exit. Once the passengers arrive at the door exit with their carry-on baggage, the crew members would (a) forcibly remove carry-on baggage at an exit, (b) throw carry-on baggage outside the aircraft, or (c) allow passengers to take their baggage with them. When the crew members forcibly remove carry-on baggage at an exit, the baggage may block the exit, or the crew may get injured while relocating the baggage away from the exit (Civil Aviation Safety Authority, 2019). The NTSB (2000) found that some passengers throw the baggage down the slide when they arrive at the exit with baggage and realize that they cannot evacuate with the baggage. This behavior may injure other people outside the aircraft or damage the ground equipment (Civil Aviation Safety Authority, 2019). Lastly, allowing passengers to take their baggage could damage the slides or create a pile of obstacles at the base of the slide (Civil Aviation Safety Authority, 2019).

Numerous studies have been conducted to optimize aircraft emergency evacuation in order to maximize the survivability of the passengers on-board (Choochart & Thipyopas, 2020; Deng, 2016; Liu & Deng, 2020; Miyoshi et al., 2012; Togher et al., 2009; Zhi-ming et al. 2014). For example, Zhi-Ming et al. (2014) studied a finer-grid aircraft evacuation model of a Boeing 777 and suggested that the evacuation efficiency significantly reduced in fire simulations. However, passengers evacuating with carry-on baggage were not considered in these studies for the simplicity of the simulation. In fact, only a few studies have considered the effect of baggage in their literature (Capote et al., 2012; Chang & Yang, 2011; Chen et al., 2020).

Chang and Yang (2011) evaluated a specific accident, China Airlines Flight CI-120, on August 20, 2007, where a Boeing 737-800 departing from Taoyuan Airport exploded soon after landing at Naha Airport. By interviewing the passengers from the accident, the researchers found that carry-on baggage was the main factor that delayed the evacuation process by acting as obstacles.

Capote et al. (2012) simulated human behavior during an evacuation in passenger trains. In the study, the probability of passengers' delay time to pick up bags was defined as:

$$P_t = P(t \neq 0|SC) \tag{2}$$

SC is a passenger standing in front of the baggage compartment. Equation 2 shows that P_t, the probability is larger than 0 due to SC. Capote et al. (2012) collected data during evacuation drills and found that the mean for t was 4.38 and the standard deviation was 2.15. Overall, the results suggested that the evacuation efficiency strongly depends on passengers' actions, such as baggage-retrieval, that may hinder the movement of passengers in the same aisle (Capote et al., 2012).

Chen et al. (2020) used the cellular automaton (CA) model to analyze the effects of luggage at a railway station. The results supported that as the initial space occupancy increased, the number of passengers with baggage had more effect on the increased evacuation time. Chen et al. (2020) further suggested that when 50% or more pedestrians evacuate with luggage, it is quicker to carry them rather than leaving them due to the obstacles from abandoned luggage.

A review of these studies revealed that the efficiency of aircraft emergency evacuation is often studied by researchers using different simulation methods. Despite the substantial number of passengers evacuating with carry-on baggage, there is limited research concerning the effects of carry-on baggage in an aircraft evacuation. According to Stedmon et al. (2017), aircraft evacuations are distinctively different from train evacuations, so a clear understanding of aircraft evacuations is vital. Specifically, no research was found that used agent-based modeling to simulate aircraft evacuation considering carry-on baggage, which indicated substantial gaps in the research of the effects of carry-on baggage in aircraft evacuations. Thus, H1 was proposed:

Hypothesis 1. There is a significant effect of the percentage of passengers evacuating with carry-on baggage (IV) on the passenger deplaning time (DV).

There is also a need to consider other factors that affect the efficiency of evacuating with passengers evacuating with carry-on baggage. The current study focused on the efficiency of aircraft evacuation with passengers' evacuating with carry-on baggage at different exit selection choices.

Exit Selection Choices

Exit selection choices are the methods that the passengers choose their exits. Not all emergency exits would be available at the aircraft evacuations. According to the Royal Aeronautical Society (2018), many accidents had less than 50% of available exits, including the Trans World Airlines Flight 843 accident in 1992. Inappropriate exit selection choices could delay the overall evacuation process. Togher et al. (2009) conducted a questionnaire with a sample size of 459 to investigate the passengers' decision-making process to choose their exits in an aircraft evacuation. Togher et a. (2009) suggested that the poor exit selection process comes from the lack of understanding of the aircraft exit location and configuration, where 25% of the participants were not aware of the location of the exits.

Three types of exit selections were discussed in this review: (a) the closest exit selection, (b) equal distribution selection, and (c) the shortest queue selection. The *closest exit selection* refers to the passengers' choosing the closest exit from their seats to evacuate. Galea et al. (2006, as cited in Deng, 2016) suggested that 86% of the passengers chose the closest exit during an aircraft emergency evacuation. However, the closest exit may not be the optimum method due to the delay caused by passengers evacuating with carry-on baggage. For instance, passengers could drop their carry-on baggage near the exit area, and the piled obstacles could create congestions and block the pathway of the exits.

Equal distribution selection is when the passengers choose the exit with an equal probability, which means that they would randomly select the exit. Liu et al. (2019) investigated the effect of instructions on emergency evacuations at an airport and supported that the shortest queue selection significantly took shorter than the equal distribution selection. Besides, Liu and Deng (2020) used ARENA on an Airbus A380 configuration and found that the shortest queue selection was significantly more efficient than equal distribution selection. Choochart and Thipyopas (2020) compared four exit selection choices for Airbus A330-300 evacuation based on exit availability: (a) evacuate freely, (b) evacuate divided by area, (c) closest exit selection, and (d) equal distribution selection. When all exits were available, the closest exit selection was the optimum method. However, by simulating various exit availabilities, the researchers suggested that the optimum exit selection choice was to evacuate freely.

In terms of the *shortest queue selection*, passengers will be assigned to the exit with the shortest queue. According to Australia Transportation Safety Board (as cited in Liu & Deng, 2020), flight crew giving commands to instruct passengers at emergency significantly improved the evacuation process during starting, exit selection, and sliding. The current study implemented the closest exit selection and the shortest queue selection. Thus H2 and H3 were proposed:

Hypothesis 2. There is a significant effect of exit selection choice (IV) on the passenger deplaning time.

Hypothesis 3. There is a significant interaction between the percentage of passengers evacuating with carry-on baggage (IV) and the exit selection choice (IV) on the passenger deplaning time (DV).

Simulation and Modeling

Simulations are an essential tool to study emergent situations as carrying out evacuation experiments using human participants in real life can be extremely expensive and risky. Simulation of aircraft accidents supports and enhances the tests by carrying out statistical analysis (Miyoshi et al., 2012). The existing evacuation models are generally classified into two classes: the discrete event and the continuous model (Kang et al., 2019). The CA model and Arena use discrete event, whereas agent-based models (ABM) are capable of modeling continuous space to simulate evacuation scenarios.

Cellular Automaton Model

The CA model is a classic example of a discrete model. In the CA model, the simulated space is divided into various uniform distributed grids, and the pedestrians at each discrete grid make actions based on the pre-determined moving rules (Kang et al., 2019). One of the greatest advantages of CA is that the simulation results are much more intuitive; it is well visually represented by the macroscopic behavior. In addition, CA models have been greatly used to simulate pedestrian dynamics from their flexibility, efficiency, and simplicity (Alizadeh, 2011). Nominally deterministic CA models are simple to implement and easy to understand the phase changes and emergence (Clarke, 2017). Powerful computation engines also allow efficient computation of the models

(Santé et al., 2010).

On the other hand, one of the main limitations is that the CA models absorb immense amounts of computer time, and therefore take years of work to make accurate predictions (Clarke, 2017). Therefore, CA is unsuitable for modeling more complicated systems with longer-range interactions, such as social and demographic models. Besides, Marques-Pita and Rocha (2011) pointed out that the results may contain redundant or unimportant information as too much attention is paid to the ‘spots’ and ‘stripes’ of the complex patterns of CA.

Many studies examined evacuation efficiency using the cellular automaton model, considering factors such as people with disabilities (Kontou et al., 2018), queuing problems at exits (Zhao et al., 2019), and crowed behavior (Zhao et al., 2015). One study considered the effects of luggage, which will be further reviewed in this chapter (Chen et al., 2020).

Arena

Arena was created by Rockwell Automation for Discrete Event Simulations (DES) in a variety of industries, including evacuation simulation (Arena, n.d.). Arena uses a flowcharting methodology to build a model, allowing easier validation and debugging process (Altiok & Melamed, 2010). Researchers found it beneficial to use this software to understand system behavior and to improve system performance by evaluating it (Ginting, 2019). Liu and Deng (2020) used Arena® 14 to simulate the aircraft evacuation model. Ginting (2019) also used Arena to simulate the evacuation model of a shopping center.

Agent-Based Model

ABM is a dynamic model that simulates how individuals interact with other individuals and the space around them to make decisions (Bone, 2018). In ABM, *agents* are the objects that may represent individual players such as vehicles, products, or people with reactive and proactive characteristics with learning capacity and spatial awareness (Grigoryev, 2018). Agents are not cellular automata as they do not live in discrete space. Therefore, the space of the agents is continuous such as a geographical map or a facility floor plan (Grigoryev, 2018).

Li et al. (2014) defined three steps of the pedestrian evacuation process: (a) perception, (b) decision-making, and (c) action. In terms of perception, agents collect information by interacting with others. In the decision-making process, agents choose the optimum evacuation route based on the perception. The last step of the pedestrian evacuation process is action; pedestrians' specific behavior rules are consistent according to the social force model.

Advantages of ABM. ABM is considered a bottom-up model, where simulated patterns come from the agents' bottom-level behaviors (Bone, 2018). In the bottom-up model, the modeling process starts from realization, modeling perspective, and formalizing processes (Balogh et al., 2020). In the realization process, researchers explore the real situation. In the modeling perspective process, the researchers determine the level of abstraction and the details. The researchers then select the correct modeling language in the formalism process. Therefore, ABM can emulate how particular decisions influence higher-level system properties.

Besides, ABM can assimilate stochastic occurrences and integrate the complexity of how agents make decisions. Therefore, researchers can run a model multiple times to analyze the likelihood of particular trends in the existing environmental constraints. Overall, ABM can simulate any or all of the periods during a short period of modeling, allowing researchers to analyze the experiments and realistically test the hypotheses without costly investments (Balogh et al., 2020).

Disadvantages of ABM. Some challenges also exist to develop models in ABM. First, computational resources are required to run a model over a reasonable period of time to reflect a process capture system stochasticity (Bone, 2018). Vigorously building an ABM can overshadow the memory and processing power of different computers. Therefore, to ensure that the necessary resources are available, researchers are urged to begin from a simple model, then build to a complex model over time.

Another challenge that researchers face is that programming skills are required to develop a model that replicates reality as much as possible. It is essential to write computer codes and identify agent behaviors to program a realistic model. Since the National Academy of Science Colloquium addressed this topic in 2001, ABM has made major advancements in providing open-source resources (An et al., 2020). For instance, ABM software such as AnyLogic provides a pedestrian model library with ABM examples, such as the aircraft boarding model.

Anylogic

AnyLogic is an ABM software developed by the AnyLogic Company with the ability to use graphical modeling language and Java code to create models. By using Anylogic, researchers can get the probability of the expected events and suggest new perspectives to the problem (Balogh et al., 2020). Organizations such as the Airbus Group, National Aeronautics and Space Administration, British Airways, as well as

FedEx used this software to build their models (Anylogic, n.d.a). The current study also used the AnyLogic to simulate the model.

Pedestrian Library. Pedestrian library is a simulation tool that helps researchers to model and evaluate how crowd movements behave in an environment and remove any potential inefficiencies (Anylogic, n.d.b). Each agent or pedestrian moves based on the physical rules in Anylogic (Yang et al., 2014). They interact with nearby objects such as walls or other pedestrians to prevent collisions. The models collect data such as the density of pedestrians and measure and visualize the load efficiency at service points (Yang et al., 2014). For these characteristics, the pedestrian library tool is often used to optimize pedestrian movement, queue behavior, and service point operations (Anylogic, n.d.b).

Social Force Model. Anylogic pedestrian library tool uses the social force algorithm dedicated to simulating pedestrian flows in a shopping mall, airport, train station, and so on (Anylogic, n.d.b). The *social force model* represents a continuous model that considers the interactions between pedestrians and other forces, so the movement of each pedestrian is regulated by Newtonian mechanics (Kang et al., 2019). The social force model allows researchers to simulate realistic pedestrian behavior under non-panic evacuation situations (Li et al., 2014). It has a benefit over the discrete models as it considers both physical and psychological interactions among individuals (Kang et al., 2019). By evaluating the surrounding space and making decisions, each agent prevents collisions with other objects (Anylogic, n.d.b).

Helbing et al. (2000) suggested the social force model, where a combination of physical and psychological forces reflects motivations and consequences for a pedestrian crowd. Equation 1 shows that each pedestrian i moves to the target velocity v_i^0 in the direction e_i^0 with mass m_i, so adapt their actual velocity v_i with a certain amount of time τ_i. The pedestrian is modeled by interaction forces f_{ij} and f_{iW}, maintaining distance from other pedestrians j and walls W (Helbing et al., 2020).

$$m_i \frac{dv_i}{dt} = m_i \frac{v_i^0(t)e_i^0(t) - v_i(t)}{\tau_i} + \sum_{j(\neq i)} f_{ij} + \sum_W f_{iW} \quad (1)$$

The interaction forces are the physical forces from counteracting body compression and sliding friction and the psychological force from each other's distance (Helbing et al., 2000).

Human Behaviors at Aircraft Evacuation

In an extreme situation such as an aircraft emergency, passengers show different behaviors such as panic, stress, intense anxiety, and startle effect; these behaviors lead to a challenging environment to evacuate.

Panic Behavior

The amount of panic is determined by the time left, waiting time, and the difficulty to find an exit (Miyoshi et al., 2012, p. 746). Panic spreads faster, and people are more likely to be panic when they are initially clustered in one location (Wang et al., 2016). In other words, passengers can easily bring panic behavior to an aircraft, where everyone is gathered inside the aircraft. Interestingly, passengers who evacuate with their carry-on baggage were also more prone to be panic (Wang et al., 2016). Therefore, passengers evacuating with their carry-on baggage from an aircraft are susceptible to panic behavior.

Passengers with panic behavior tend to ignore instructions with maladaptive behavior such as jamming and overcrowding (Chen et al., 2019; Zhao et al., 2015).

According to Zhao et al. (2015), the packed crowd can cause severe pressures up to 4450 N/m, which is equivalent to bending steel barriers or breaking brick walls. However, the effect of panic behavior on the total evacuation time was controversial between researchers. Wang et al. (2015) supported that panic behavior decreases evacuation effectiveness. On the other hand, Li et al. (2014) suggested that panic behavior may increase evacuation efficiency. Li et al. (2014) used Java program language on AnyLogic to evaluate the effect of the number of evacuees on train evacuation efficiency. Evacuation efficiency increased with panic behavior up to 1800 evacuees, but the effect was negligible when the number of evacuees exceeded 1800 (Li et al., 2014).

Startle Effect

Startle is a pervasive autonomic response that involves both humans and a variety of other animals (Martin et al., 2015). It is an autonomic nervous system response because of a life-threatening incident, such as an aircraft emergency evacuation. The startle reflet reaction occurs instantaneously, as little as 14 msec (Martin et al., 2015). Other stress-related mechanisms are activated as startle reflex emerges. Responses such as elevated heart rate and blood pressure, and sensory stimulation, with cognitive systems may affect some degree of response within the body (Martin et al., 2015). Especially, fear-potentiated startle in evacuation could impair decision-making and situation awareness, affecting passengers to evacuate with carry-on baggage.

The startle effect could also decrease the overall evacuation efficiency. According to the Air Accident Investigation Branch (1988, as cited in Stedmon et al., 2017), passengers freezed as soon as the aircraft emergency began, and particularly, older women were more susceptible to such behavior. According to Martin et al. (2015), startle could cause a delay in information processing for up to 30 sec.

Theoretical Framework and Hypotheses

Application of the Structural Equation Modeling

SEM is a general linear statistical model that can be used to statistically analyze most research hypotheses for social scientists (Hoyle, 1995). SEM adopts a confirmatory approach and identifies the causal processes through structural equations, and these structural relationships can be modeled visually to conceptualize the theory under study (Byrne, 2010). A wide variety of models can also be accommodated by SEM, including models with latent variables (Byrne, 2010). Latent variables are the factors that cannot be specifically calculated, such as perceived risk or awareness. By using latent variables, researchers can consider the unreliability of measurements (Ledermann & Kenny, 2017).

SEM has its advantage over regression models, which provide coefficients that approximate the statistical importance of the structural association between theoretical constructs (Mayhew et al., 2009). SEM has also been widely used by researchers with the application of the TPB (Mayhew et al., 2009; Pan & Truong, 2018; Zhou et al., 2016). Through SEM, the current study could validate the modified TPB to find the behavioral intentions of passengers evacuating with carry-on baggage.

Theory of Planned Behavior

It is crucial to understand the human behavior of evacuating with carry-on baggage at aircraft emergencies in order to optimize the aircraft evacuation efficiency since these factors cannot be simulated. Icek Ajzen suggested TPB as conceptual frameworks to study human behaviors (Ajzen, 2002a). The theory suggested three factors that affect human behavior: (a) behavioral beliefs, (b) normative beliefs, and (c) control beliefs (Ajzen, 2002a). According to Ajzen (2002a), “behavioral beliefs produce a favorable or unfavorable attitude toward the behavior, normative beliefs result in perceived social pressure or subjective norm, and control beliefs give rise to perceived behavioral control (PBC), the perceived ease or difficulty of performing the behavior” (p. 665).

The theory is widely used in the aviation industry to determine the behavioral intentions of individuals, especially to understand the customers’ purchase intentions (Maichum et al., 2016; Pan & Truong, 2018; Tan et al., 2017). However, it has minimal application in the investigation of behavioral intentions regarding safety-related behaviors. Chang (2012) applied TPB to passengers' behavioral intentions with reduced mobility and reported differences in intentions due to variation in PBC and subjective norms. Zhang et al. (2019) applied TPB in emergencies but was used to predict customer intention to eat poultry during the H7N9 emergency, which did not provide behavioral intentions regarding safety-related behaviors.

Few studies applied the TPB to predict violation behaviors. Fogarty and Shaw (2010) studied violation behaviors of aircraft maintenance and further recommended to use TPB to understand the psychological background of the incident-related violations. Zheng et al. (2018) applied TPB to predict Chinese drivers’ intentions in illegal emergency lane parking. In this study, TPB was applied to examine how attitude, perceived value of the baggage, perceived risk, and awareness can influence the behavioral intention of evacuating with carry-on baggage. Table 1 shows the operational definitions of the factors in the TPB model. All hypotheses were derived from previously validated relationships using TPB, although the factors were modified in a new way to fit the study context. Figure 1 shows the research model for passengers' intentions to evacuate with carry-on baggage. The predictor variables were attitude, perceived risk, perceived value of luggage, and awareness. The outcome variable was passengers' behavioral intentions to evacuate with carry-on baggage.

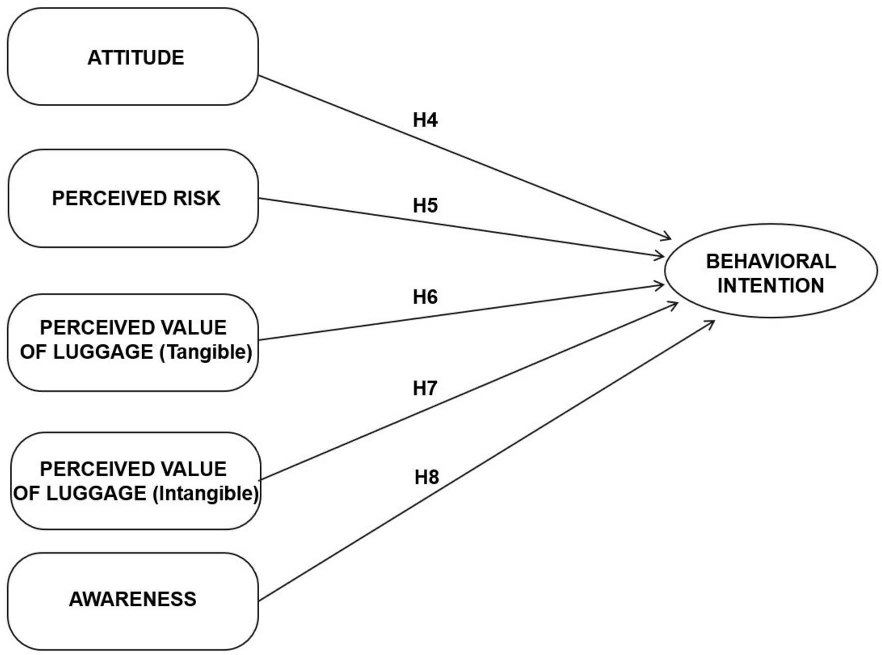
Table 1

Construct Definitions

Factor	Operational definition	Adopted from
Attitudes	Passengers' favorable or unfavorable opinions toward the behavior of evacuating with carry-on baggage	Ajzen (2002a)
Perceived value of baggage	Passengers' overall evaluation of the tangible and intangible products based on perceptions of what is in the carry-on baggage	Meng and Cui (2020)
Perceived risk	Risk-as-feeling approaches by personalizing the risk associated with the immediate incident	Kinateder et al. (2015)
Awareness	Having a particular interest in or experience of the rules of passengers' evacuating with carry-on baggage	Bashir et al. (2019)

Figure 1

Research Model



Attitude

An individual's attitude comes from behavioral beliefs and eventually leads to behavioral intention (Ajzen, 2002a). In other words, an attitude towards a behavior is determined by a strong belief in the consequences and an assessment of the outcome (Fogarty & Shaw, 2010). Attitude was used as a variable for some researchers that applied TPB in safety-related behaviors (Fogarty & Shaw, 2010; Zheng et al., 2018). Fogarty and Shaw (2010) suggested that the formation of employees' own attitudes and group norms were specifically influenced by perceptions of management attitudes. Zheng et al. (2018) found that drivers with higher education were more negative about illegal emergency lane parking than drivers with less education. In Zheng et al.'s study (2018), attitude was not significantly related to intentions. However, attitude was the strongest predictor of intentions in a meta-analysis conducted by Armitage and Conner (2001). Also, many researchers found a significant positive relationship between attitude and behavioral intentions (Bashir et al., 2019; Pan & Truong, 2018; Zhang et al., 2019). Thus, H4 was proposed:

H4: Attitudes are positively related to passengers' intentions to evacuate with carry-on baggage.

Perceived Risk

Perceived risk is the feeling of danger that people experience due to an incident or an accident (Sherman et al., 2001). That is how the evacuees feel "at-risk" in the evacuation (Kuligowski, 2011). 'Risk' has different definitions, such as hazard, consequence, probability, or potential threat (Slovic & Weber, 2002, as cited in Kinateder et al., 2015). Therefore, each participant may feel a different amount of danger in the same evacuation situation.

Studies regarding the evacuation from the September 11 attacks supported the effect of perceived risk on evacuees' behavior (Kuligowski, 2011; Sherman et al., 2011). Kuligowski (2011) found that perceived risk predicted decisions during evacuation. Also, pedestrians with lower perceived risk took longer pre-evacuation delays (Sherman et al., 2011). The behavioral intention to evacuate with carry-on baggage may differ depending on the amount of risk each passenger perceives. Zhou et al. (2016) validated the relationship by using perceived risk as a factor that affects pedestrians' violating crossing behavioral intention.

Therefore, H5 was proposed:

H5: Perceived risk is negatively related to passengers' intention to evacuate with carry-on baggage.

Perceived Value of the Baggage

Perceived value was often used in tourism and hospitality researches (Meng & Cui, 2020; Morosan & Defranco, 2016; Prebensen & Xie, 2017). *Perceived value* is what people perceive from the overall assessment of a tangible or intangible product (Meng & Cui, 2020). According to Statistica (2014), the top five carry-on essentials for passengers in the United States (U.S.) were reading materials, followed by medication, iPad/tablet, snack, and hand sanitizer. Tangible product is a physical object that can be perceived by touch, such as a phone or food. Most goods are tangible products. Intangible product can only be perceived indirectly, such as information in a mobile device, including photos and reading materials. The perceived value of the carry-on baggage may vary depending on the tangible and intangible product and the passenger. Depending on the perceived value of the baggage, the behavioral intentions to take their carry-on baggage can vary. Thus, H6 and H7 were proposed:

H6: Perceived value of tangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H7: Perceived value of intangible items is positively related to passengers' intention to evacuate with carry-on baggage.

Awareness

Awareness is the understanding of particular items and information (Aziz & Chok, 2013, as cited in Bashir et al., 2019). The relationship between awareness and behavioral intention was validated by Bashir et al. (2019). The awareness of a product affected the customers' decisions towards buying the product. In the context of aircraft evacuation, passengers may not be aware of the dangers involved with retrieving luggage during an evacuation (Civil Aviation Safety Authority, 2019). Many evacuations have demonstrated that people continue to pick up their carry-on bags during an evacuation, even after the cabin crew has constantly told them to leave their baggage. A survey conducted by the University of Coventry in 2017 found that 34% did not know about the rule to leave baggage in an evacuation, 34% knew that they should leave bags, and 32% did not know about the rules but assumed that leaving bags was sensible (Prew, 2017). However, the relationship between awareness and passengers' intention to evacuate with carry-on baggage was not identified.

Thus, H8 was proposed:

H8: Awareness is negatively related to passengers' intention to evacuate with carry-on baggage.

Summary

Overall, this chapter reviewed simulation and modeling, existing literature on carry-on baggage and exit selection choices, and human behaviors at evacuation. Chapter II examined a wide variety of studies on discrete and continuous evacuation models. Advantages of the continuous model were identified, and the reason why Anylogic was selected as the simulation software was explained. The review of the literature highlighted comparative studies regarding carry-on baggage. Although some studies examined the effects of carry-on baggage and exit selection choices separately, no study has concurrently investigated the effects of carry-on baggage and exit selection choices at aircraft evacuations. There is a need to examine the effects of carry-on baggage and exit selection choices on aircraft evacuation efficiency.

This chapter also reviewed the theoretical framework, SEM and TPB, and determined that they are suitable for the current research. The importance of the constructs, including attitudes, perceived value of luggage, perceived risk, and awareness, were also reviewed. The constructs were modified to reflect the research questions related to passengers' intention to evacuate with carry-on baggage. Based on the current literature on TPB, the selection of external factors was justified. The research design and methodology were outlined in Chapter III, including data collection and sources of the data.

Chapter III: Methodology

This study aimed to investigate the effects of carry-on baggage on evacuation efficiency and understand the passengers' intentions to evacuate with carry-on baggage. This study included two parts to examine the effects of passengers evacuating with carry-on bags. Research study 1 simulated the effect of carry-on luggage on aircraft evacuation using agent-based models. In addition, research study 2 captured responses to determine the factors affecting passengers' behavioral intention to evacuate with carry-on baggage. Chapter III starts by describing the research methods, including research design, population and sample, sources and treatment of the data, and the baseline model validation. It also provides information for future researchers to replicate the study.

Study 1 (Simulation)

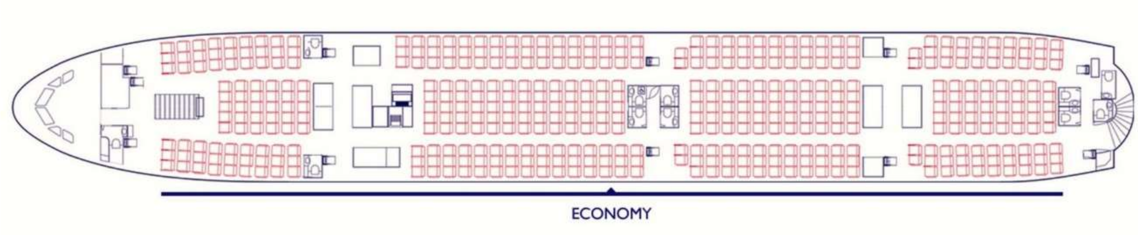
The simulation model was developed using AnyLogic to understand the relationship between passengers evacuating with baggage and exit selection choice with evacuation efficiency. The model structure of aircraft evacuation and the baseline model validation are discussed in Chapter III.

Apparatus and Materials

This study was conducted to analyze the aircraft evacuation process of an A380 model using AnyLogic. Only the first floor of the Airbus A380 with 465 seats was considered in the simulation, containing all economy seats. The aircraft configuration used in the simulation is shown in Figure 2. Data were directly collected from the software into a Microsoft Excel spreadsheet. Finally, the IBM Statistical Package for Social Sciences (SPSS) software was used to process the data collected from the software to test the null hypotheses.

Figure 2

A380 First Level Configuration



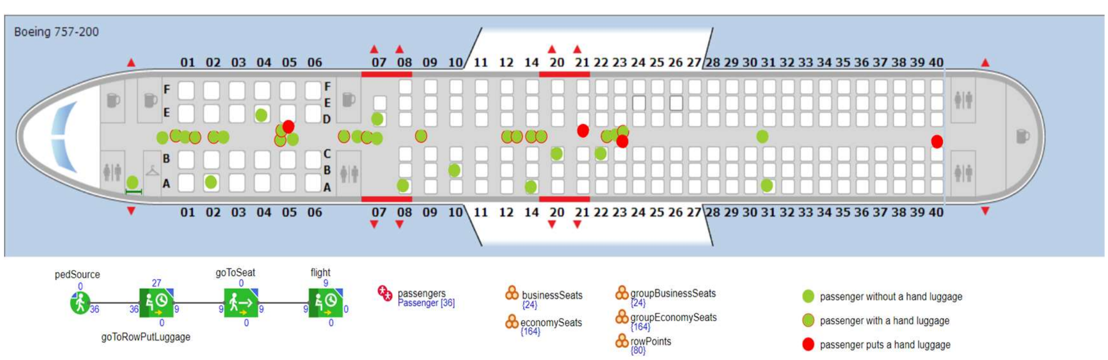
Note. Adapted from "Airbus expects 11-abreast A380 to attract new breed of customer" by M. Kirby, 2015, *Runway Girl Network.* (https://runwaygirlnetwork.com/2015/06/03/airbus-expects-11-abreast-a380-to-attract-new-breed-of-cu). Copyright by Amedeo.

Design and Procedures

The simulation was constructed based on the aircraft boarding model in the AnyLogic model library. The aircraft boarding model simulated how passengers board on the aircraft, put their luggage on the overhead compartments, and sit on their corresponding seats. Figure 3 illustrates the logic of the aircraft boarding model.

Figure 3

Aircraft Boarding Model



The researcher set the percentage of passengers with carry-on baggage at 0%, 50%, and 80%. Then, the passengers with carry-on baggage were randomly assigned to a seat. In the beginning, passengers were assigned a number from 0 to 464, which corresponded to their seat number. Passengers then entered the aircraft, stopped at the corresponding row, and put their carry-on luggage in the overhead compartments. After all the passengers were seated, the evacuation process started. The two exit selection choices, the shortest queue choice and the closest queue choice, were be compared with different percentages of passengers with carry-on baggage. The total evacuation time was measured from the start of the evacuation until the last passenger left the aircraft.

A two-way between-subject analysis of variance (ANOVA) was used as the research method. The first IV was the percentage of passengers evacuating with carry-on bags with three levels: 0%, 50%, and 80% of passengers evacuating with carry-on baggage. The second IV was the exit selection policy with two levels: the shortest queue policy and the closest exit policy. The DV was the evacuation efficiency, measured as passenger evacuation time in seconds. The variables are shown in Figure 4.

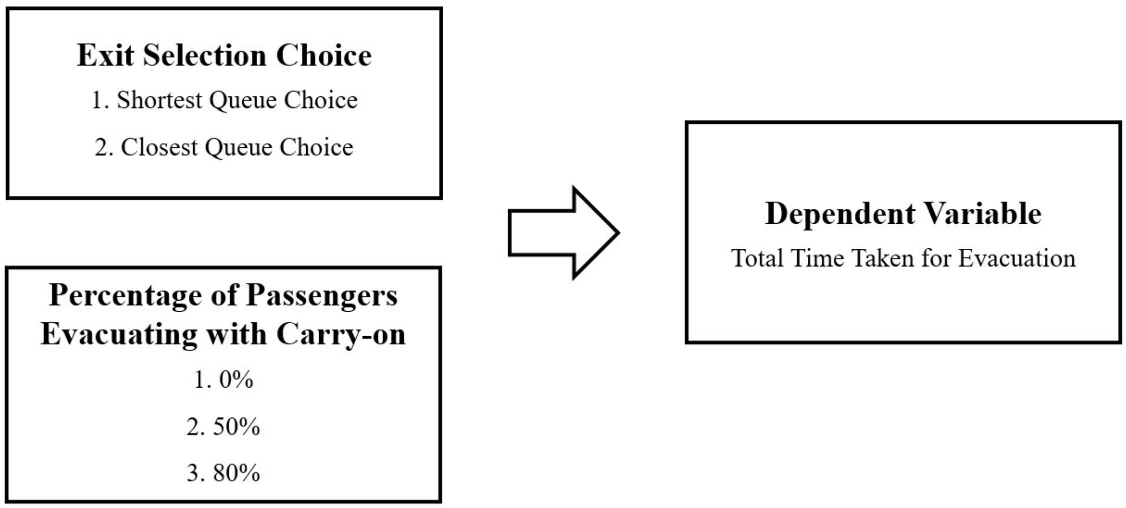
There were six evacuation scenarios based on the IVs:

- Shortest queue selection, 0% of passengers evacuating with baggage
- Shortest queue selection, 50% of passengers evacuating with baggage
- Shortest queue selection, 80% of passengers evacuating with baggage
- Closest queue selection, 0% of passengers evacuating with baggage
- Closest queue selection, 50% of passengers evacuating with baggage
- Closest queue selection, 80% of passengers evacuating with baggage

Each scenario was tested 50 times, and the results were exported to SPSS.

Figure 4

The Independent and Dependent Variables for Study 1



Hypothesis Testing

The following null hypotheses were evaluated using a 2 x 3 between-subjects ANOVA. The significance level was set at 5%. The post-hoc tests were run for any significant interaction and main effects.

$H_0$1: There is no significant effect of the percentage of passengers evacuating with carry-on baggage (IV) on the passenger deplaning time (DV).

$H_0$2: There is no significant effect of exit selection choice (IV) on the passenger deplaning time.

$H_0$3: There is no significant interaction between the percentage of passengers evacuating with carry-on baggage (IV) and the exit selection choice (IV) on the passenger deplaning time (DV).

Sources of the Data

The social force model determined passengers' walking speed. The slide down time was set as a triangular distribution of [0.50, 0.60, 0.90], and the unit was in seconds (Motevalli et al., 2008; as cited in Liu & Deng, 2020). According to the Royal Aeronautical Society (2018), there were accidents where less than 50% of exits were available, including the Trans World Airlines Flight 843 accident in 1992. Therefore, only 50% of the emergency exits and slides were available in the simulation as in real accidents.

Baseline Model Validation

A real-life evacuation drill performed by Airbus in 2006 under the control of the FAA and the European Aviation Safety Agency was able to evacuate all passengers within 78.04 s (Ghedini, 2011). The evacuation drill also utilized 50% of the exits, and the flight crew guided the passengers to the exit with the shortest queue. This real-life evacuation drill was used as a baseline model. A t-test was used to validate the baseline model by comparing the average evacuation time of the simulation to the actual data and seeing if there is a significant difference between them. An alpha level of .05 was used for the *t*-test.

Study 2 (Survey)

Study 2 gathered survey responses to model passengers' behavioral intentions regarding evacuation with carry-on baggage. Study 2 used a survey approach to help answer the human behavioral aspects that simulation could not answer. The model was developed based on the Theory of Planned Behavior (TPB), thus followed deductive reasoning.

Research Method Selection

SEM was used as a statistical method to incorporate factor analysis. As mentioned in Chapter II, SEM is a research method that can effectively analyze the relationship between latent variables. Therefore, the current study used SEM to analyze the factors that affect passengers' behavior to evacuate with carry-on baggage.

A survey is an appropriate research method to gather subjective data regarding passengers' attitudes, beliefs, and values (Vogt et al., 2012). In addition, SEM required a relatively large number of sample size. Therefore, a survey was conducted to gather a high percentage of respondents to answer the questions (Vogt et al., 2012). Short and precise survey questions were created based on Ajzen's guide for conducting a TPB questionnaire (Ajzen, 2002b).

Population/Sample

The target population was set as residents of the United States that are 18 years or older and have flown in an aircraft before. The non-probability convenience sampling method was used as the sampling strategy. SEM analysis generally requires large sample sizes, and researchers suggested various sample sizes depending on the number of indicators. Kline (2015) recommended using 20:1 as the ratio of sample size. For example, a study with 10 parameters should have a minimum of 200 as a sample size. Researchers often mentioned 300 as an adequate sample size (Comrey & Lee, 2013; Tabachnick et al., 2007). As a simple model, the current study used 300 as the sample size.

Apparatus and Materials

The survey was conducted online through the Amazon Mechanical Turk (MTurk) website. Online recruiting was an affordable option for selecting participants outside the university, which enabled the recruitment of various participants that reflected the U.S. population (Chandler et al., 2019). MTurk was a widely used online survey tool by behavioral researchers to obtain reliable data (Chandler et al., 2019). Each participant who completed the survey was paid $1.00. IBM SPSS Analysis of Moment Structure (AMOS) version 26 was used to analyze the data.

Design and Procedures

The questionnaire included previously validated questions and questions customized to fit the context of evacuation with carry-on baggage. The questionnaire was broken down into three sections. The first section asked the filter questions – *Have you ever traveled with an airline before*? *Are you eighteen years or older?* and *Do you agree to the informed consent provided?* These dichotomous filter questions tested the eligibility of the participants, so participants who were eighteen years or older, who have flown with an airline before, and agreed to the informed consent were eligible to participate in the survey.

The second section asked the passengers' demographics, including age, gender, education level, monthly income, occupation, and nationality. Each question in this section used categories. For example, education level was categorized into: lower than high school, high school, bachelor's degree, master's degree, and higher than master's degree.

The third section included questions concerning passengers' awareness and assessed the factors that could affect passengers' intentions to evacuate with carry-on bags. The factors were defined and discussed in Chapter II. Five Likert-type scale items were used to measure the factors.

Ethical Consideration

As the survey involved personal information, ethical considerations were addressed through (a) informed consent; (b) voluntary participation; (c) do no harm; (d) respect for anonymity, confidentiality, and dignity; and (e) only accessing information/data relevant to the study. Embry-Riddle Aeronautical University (ERAU) Institutional Review Board (IRB) requirements were met, and the approval letter was included in the appendix. The data collection, including the pilot study, started after the IRB approval.

The survey started with an informed consent form, including information such as the purpose of the survey, expected time required to take the survey, eligibility to participate in the survey, and provided a point of contact for additional information about the study. Participating in the survey was totally voluntary, and only those who agreed to the informed consent carried on to the actual survey. Participants were free to skip any question they do not wish to answer to ensure protection from harm. The researcher maintained the participants' privacy by keeping the data in a password-protected computer by classifying it as confidential information.

Reliability Assessment Method

The study involved several methods to assure the reliability of the study. First of all, the survey questions were written in clear and concise wording to minimize any ambiguity. Besides, each construct included at least three questions. For each factor, the items' internal consistency was assessed for the reliability of the survey results.

Therefore a small pilot study with 30 participants was undertaken to assess Cronbach's alpha before conducting the actual survey. Cronbach's alpha is often used to calculate the reliability of the multi-item scale. Cronbach's alpha ranges from 0 to 1, and the internal consistency increases as it gets closer to 1 (Vogt et al., 2012). Items with Cronbach's alpha smaller than .70 would be updated.

Validity Assessment Method

Face validity and construct validity were assessed in this study. Face validity determined how well the questionnaire was developed, so the items measured the right thing. Face validity was assured by having the subject-matter experts review and provide feedback about the wording and structure of the questions. Construct validity measured how well the model fits the data. The Confirmatory Factor Analysis (CFA) would ensure validity by evaluating a priori hypothesis on the items (Zhou et al., 2016). CFA was conducted in IBM SPSS AMOS 26 by using the principle component analysis method.

Data Analysis Process/Hypothesis Testing

IBM SPSS version 24 and IBM SPSS AMOS version 26 were used to analyze the data. First, descriptive statistics were conducted to summarize demographic data and individual constructs. Then, a two-step approach was adopted, which were CFA and SEM. CFA was conducted to validate the measurement model. Then, SEM analysis was carried out to find the relationship between the constructs and test the alternative hypotheses.

H4: Attitudes are positively related to passengers' intentions to evacuate with carry-on baggage.

H5: Perceived risk is negatively related to passengers' intention to evacuate with carry-on baggage.

H6: Perceived value of tangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H7: Perceived value of intangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H8: Awareness is negatively related to passengers' intention to evacuate with carry-on baggage.

Summary

Overall, a simulation and a survey were carried out together to examine the factors affecting behavioral intentions of evacuating with carry-on baggage and the overall effect of passengers evacuating with carry-on baggage. The simulation model was developed using AnyLogic. The simulation was based on the aircraft boarding model of an Airbus A380, and the model was validated by comparing the average evacuation time of the simulation to the actual data. A two-way ANOVA was then conducted to test the effect of carry-on baggage and exit selection choice on the total evacuation time.

The survey was conducted through Amazon MTurk. Ethical considerations were assessed, and the data collection started after the IRB approval. Reliability was assured by testing Cronbach's alpha, and the validity was assured by face validity and construct validity. IBM SPSS and IBM SPSS AMOS were used to analyze the CFA and SEM. Chapter IV presented the analytical results in more detail.

Chapter IV: Results

This chapter presents the results of the two parts of the study. Results for Study 1 include three sections: baseline model validation results and experiment results. Results for Study 2 include four sections: pilot study results, descriptive statistics, CFA, and SEM.

Study 1 Results

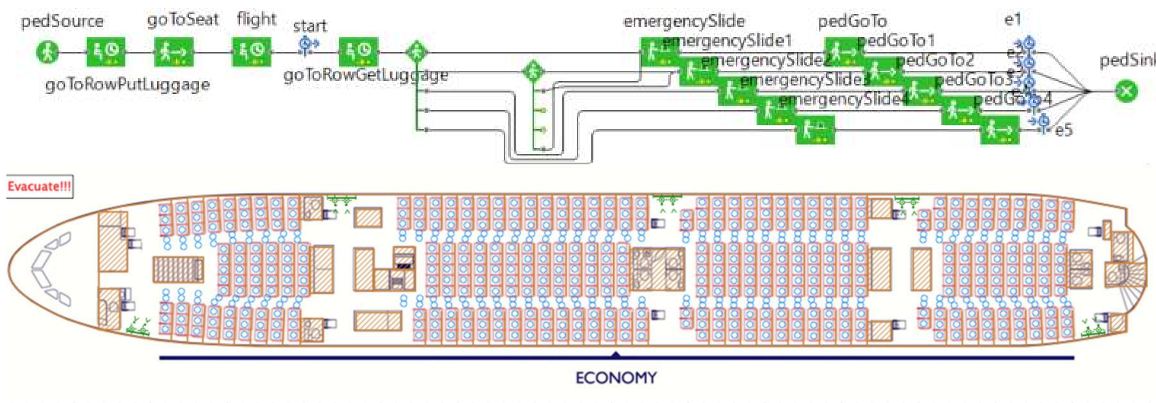
Baseline Model Validation Results

A one independent sample *t*-test was used to validate the baseline model by comparing the average evacuation time of the simulation to the actual data and see if there is a significant difference between them. As mentioned in Chapter 3, actual data were gathered from a real-life evacuation drill performed by Airbus in 2006. All passengers were able to evacuate an Airbus A380 within 78.04 seconds (Ghedini, 2011). The evacuation drill also utilized only 50% of the exits, and the flight crew guided the passengers to the exit with the shortest queue.

A one independent sample t-test was not significant at an alpha level of .05, with $p = .142$. There was no significant difference between the validation model and the mean of the model. Therefore, the baseline model was considered validated. Figure 5 illustrated the logic of the baseline model from Anylogic.

Figure 5

Screenshot of the Logic from AnyLogic



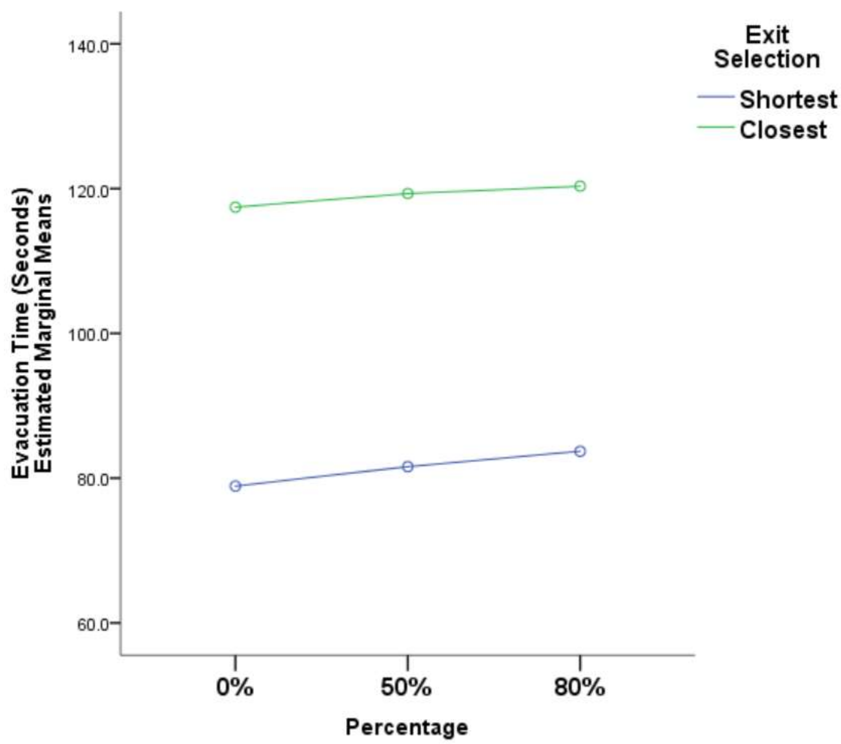
Two-way Between Subjects ANOVA

A two-way ANOVA was conducted to examine the effects of the percentage of passengers evacuating with carry-on baggage and exit selection choice on evacuation time. Residual analysis was performed to test for the assumptions of the two-way ANOVA. Outliers were assessed by inspection of a boxplot. Normality was assessed using Shapiro-Wilk's normality test for each cell of the design, and homogeneity of variances was assessed by Levene's test. No significant outliers were observed as assessed by inspection of a boxplot. Residuals were not normally distributed ($p < .05$), thus there the assumption of normality was violated. According to Maxwell & Delaney (2004), ANOVAs are considered fairly robust to deviations from normality in terms of a Type I error. Therefore, no adjustments were made. The assumption of the equality of variance was also tested. Levene's test of equality of variance was significant ($p < .05$), and thus unequal variances were assumed.

The interaction effect between percentage of passengers evacuating with carry-on baggage and exit selection choice was not statistically significant, $F(2, 294) = .480$, $p = .619$, partial $\eta^2 = .003$. See Figure 6. Therefore, an analysis of the main effect for the percentage of passengers evacuating with carry-on baggage was performed, which indicated that the main effect was statistically significant, $F(2, 294) = 21.197$, $p < .001$, partial $\eta^2 = .126$, a large effect size. All pairwise comparisons were reported 95% confidence intervals, and *p*-values are Bonferroni-adjusted. Using the Bonferroni post hoc, the mean evacuation time for 0% was significantly lower than 50% and 80% ($p < .001$). However, the mean evacuation time for 50% was not significantly lower than 80% ($p > .05$).

Figure 6

Mean Evacuation Time for Exit Selection Choices Based on Percentage



The main effect for the exit selection choice was also found statistically significant, $F(1, 294) = 8770.400$, $p < .001$, partial $\eta^2 = .968$, which is a large effect size. The mean evacuation time for shortest queue choice ($M = 80.75$, $SD = 4.35$) was lower than the mean evacuation time for the closest exit choice ($M = 118.98$, $SD = 3.06$). Descriptive statistics are presented in Table 2.

Table 2

Descriptive Statistics for Percentage and Exit Selection Choice in Seconds

	Shortest		Closest		Total	
	M	*SD*	*M*	*SD*	*M*	*SD*
0%	78.67	3.54	117.44	2.24	98.06	19.70
50%	81.43	3.88	119.23	2.91	100.33	19.30
80%	82.15	4.80	120.28	3.30	101.21	19.60
Total	80.75	4.35	118.98	3.06	99.87	19.51

Note. M = Mean, *SD* = Standard Deviation

Study 2 Results

Pilot Study Results

The survey that measured the effect of attitude, perceived risk, perceived value, and awareness on behavioral intention to evacuate with carry-on baggage was created in Google Forms and disseminated to the participants via MTurk. A pilot study was conducted on 30 participants to test reliability. Cronbach's alpha was used to assess the internal consistency of the test items measuring the same construct. Cronbach's alpha results for all items were above .70, ranging from .851 to .902, which indicated that the scale items were consistent. Therefore, no changes were made to the survey questions. The reliability of the survey constructs and items were considered acceptable, and these items were used in the large-scale survey. Table 3 shows the question items and Cronbach's alpha results for the pilot study.

Table 3

Cronbach's Alpha Results for the Pilot Study

Construct		Item Question	α
Attitudes	AT1	Evacuating with carry-on baggage in the given scenario would be wise	.86
	AT2	Evacuating with carry-on baggage in the scenario would make me feel comfortable	
	AT3	Evacuating with carry-on baggage in the scenario will be beneficial to me	
Perceived Risk	PR1	If I evacuate with carry-on baggage in the given scenario, I will endanger my life	.88
	PR2	I will get seriously injured if I evacuate with carry-on baggage in the scenario	
	PR3	Evacuating with carry-on baggage in the scenario is more dangerous than evacuating without carry-on baggage	
Perceived Value (Tangible)	PV1	Tangible products in my carry-on baggage are precious	.88
	PV2	Tangible products in my carry-on baggage are valuable	
	PV3	Tangible products in my carry-on baggage are important	
Perceived Value (Intangible)	IPV1	Intangible products in my carry-on baggage are precious	.85
	IPV2	Intangible products in my carry-on baggage are valuable	
	IPV3	Intangible products in my carry-on baggage are important	
Awareness	AW1	I know that evacuating with carry-on baggage is prevented by cabin crew	.85
	AW2	I know that evacuating with carry-on baggage could endanger other passengers' lives	
	AW3	I know that evacuating with carry-on baggage would delay the evacuation process	
Behavioral Intention	BI1	I would evacuate with carry-on baggage as described in the scenario	.90
	BI2	If I encounter this situation in the future, I will evacuate with carry-on baggage	
	BI3	I would seriously consider evacuating with carry-on baggage in the scenario	

Descriptive Statistics

The large-scale survey aimed to achieve 300 responses. Responses who completed the survey with missing answers were removed from the data set. A total of 300 responses were completed, and 19 cases were removed while cleaning the data. In the end, 281 were available for analysis as valid responses. The completion rate of the survey was 93.67%.

Demographics. Demographic information such as gender, age, education level, monthly income in USD, occupation, and nationality was collected in the survey. Out of 281 respondents, 64.4% were male, and 35.6% were female. They were also grouped into five age categories, where most of the respondents were 21 -30 years (65.8%). Most respondents held Bachelor's degree (63.3%), and monthly income varied between 0 – 500 per month (6%), 501 – 1000 (23.5%), 1001 – 1500 (26.7%), 1501 – 2000 (18.5%), 2001 – 2500 (10.3%), and the largest category was above 2501 (14.9%). The majority of the respondents were employed full-time (91.1%). Finally, the respondents were mostly from North America (43.4%) or Asia (41.3%). Table 4 shows the demographic attributes of the participants.

Variables. Each construct was measured by three item questions. The participants were asked to answer the questions based on a 5-point Likert scale, from 1 (strongly agree) to 5 (strongly disagree). Descriptive statistics of the constructs, including mean, standard deviation, skewness, and kurtosis, were run in SPSS, and the results are shown in Table 5.

Table 4

Demographic Attributes of Participants

Attribute	Subgroup Categories	Frequency ($N = 281$)	Percentage
Gender	Female	100	35.6
	Male	181	64.4
Age	<20	0	0
	21 – 30	185	65.8
	31 – 40	51	18.1
	41 – 50	25	8.9
	51 – 60	12	4.3
	>60	8	2.8
Education	Below high school	1	0.4
	High school	7	2.5
	Bachelor's degree	178	63.3
	Master's degree	94	33.5
	Higher than Master's degree	1	0.4
Monthly Income (USD)	<500	17	6.0
	501 – 1000	66	23.5
	1001 – 1500	75	26.7
	1501 – 2000	52	18.5
	2001 – 2500	29	10.3
	2501 and above	42	14.9
Occupation	Student	5	1.8
	Part-time employment	15	5.3
	Full-time employment	256	91.1
	Unemployed	5	1.8
Nationality	North America	122	43.4
	South America	28	10.0
	Europe	15	5.3
	Asia	116	41.3
	Africa	0	0

Table 5

Descriptive Statistics Results of the Constructs

Construct	Item Question	*M* (*N* = 281)	*SD*	Skewness	Kurtosis
Attitude	AT1	2.60	1.28	0.62	-0.76
	AT2	2.64	1.36	0.47	-1.02
	AT3	2.57	1.30	0.47	-0.90
Perceived Risk	PR1	2.33	1.16	0.79	-0.08
	PR2	2.30	1.18	0.72	-0.41
	PR3	2.20	1.20	1.01	0.20
Perceived Value (Tangible)	PV1	2.42	1.15	0.54	-0.54
	PV2	2.57	1.20	0.67	-0.41
	PV3	2.40	1.19	0.67	-0.50
Perceived Value (Intangible)	PV4	2.55	1.23	0.74	-0.37
	PV5	2.46	1.18	0.57	-0.53
	PV6	2.55	1.22	0.73	-0.42
Awareness	AW1	2.21	1.13	0.78	-0.20
	AW2	2.27	1.17	0.86	-0.06
	AW3	2.11	1.13	0.94	0.05
Behavioral Intention	BI1	2.68	1.31	0.54	-0.84
	BI2	2.57	1.32	0.51	-0.92
	BI3	2.67	1.33	0.60	-0.85

Note. M = Mean, *SD* = Standard Deviation

Attitudes and behavioral intentions were the original components of the TPB model. Perceived risk and tangible and intangible perceived value were external factors added to the expanded TPB model. Overall, the mean values for all items can be described as moderate. The average between 2.20 and 2.68 would indicate between “agree” and “neutral”. Items measuring behavioral intention had the highest mean scores, and items measuring perceived risk had the lowest mean scores. Noticeably, item PR3 the factor of perceived risk, had the lowest average (*M* = 2.20, *SD* = 1.20) with a positive skew.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was used to test the reliability and validity of the variables. The CFA was performed using IBM SPSS AMOS 26. The assumption of normality was met as the absolute kurtosis values for all variables were less than 2.0, which was considered acceptable to meet the normality assumption. After the dataset was cleaned, 281 responses did not include any missing data. Therefore, no additional steps were required for missing data. Outliers were identified using Mahalanobis D-square (D^2) values. Values greater than 100 would represent extreme outliers (Kline, 2015). However, all values were less than 100, where the values ranged from 19.56 to 74.61. Therefore, the survey data met normality and outlier assumptions.

Model Fit and Adjustment. CFA was performed on the large-scale dataset, including 281 responses. Acceptance value for the model fit indices were CFI > .95, GFI and NFI > .90, CMIN/df ≤ 3.00, and RMSEA < .08 (Ahmad et al., 2016). The initial CFA model had a low model fit, with room for improvement in terms of GFI, CMIN/df, and RMSEA. Therefore, measures were taken to improve the model fit. First, the factor loading of the items was considered. All items met the .70 threshold. However, the discriminant validity showed large values for awareness (AW). Therefore, a decision was made to remove the AW to improve the model fit and validity. Then, the modification indices showed some large MI values. Two error covariances were created between error terms from the largest MI values. The final CFA model showed improvement in the model fit, X^2 = 231.780 (*df* = 78, *p* < .001), CFI = .959, NFI = .940, GFI = .878, CMIN/*df* = 2.972, RMSEA = .084. GFI and RMSEA values were slightly off the acceptance value but tolerable (Angell, 2019; Hu & Bentler, 1999). Angell (2019) claimed an RMSEA value of .09 was an acceptable threshold, and Hu & Bentler (1999) supported that although a GFI value larger than .90 is recommended, larger than .80 may be useful with caution. Therefore, it was used as the final CFA model. Table 6 compares the model fit indices before and after the model improvement. Figure 7 illustrates the initial CFA model, and Figure 8 illustrates the final CFA model.

Table 6

Model Fit Indices for Initial and Final CFA Model

Model Fit Indices	Acceptance Value	Initial CFA Model	Final CFA Model
X^2	-	445.921	231.780
df	-	120	78
GFI	> .90	**.801**	**.878**
NFI	> .90	.908	.940
CFI	> .95	.930	.959
CMIN/*df*	≤ 3.00	**3.716**	2.972
RMSEA	< .08	**.098**	**.084**

Note. GFI = Goodness of Fit Index, NFI = Normed-Fit Index, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation

Figure 7

The First Specified CFA Model

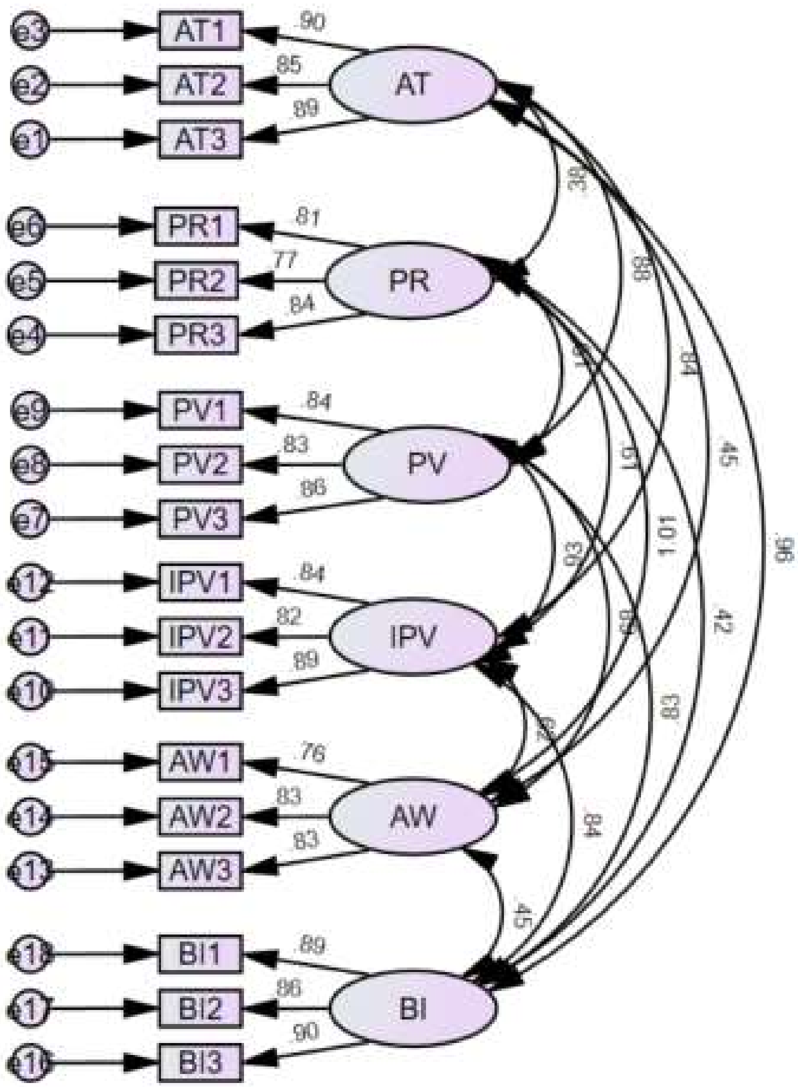
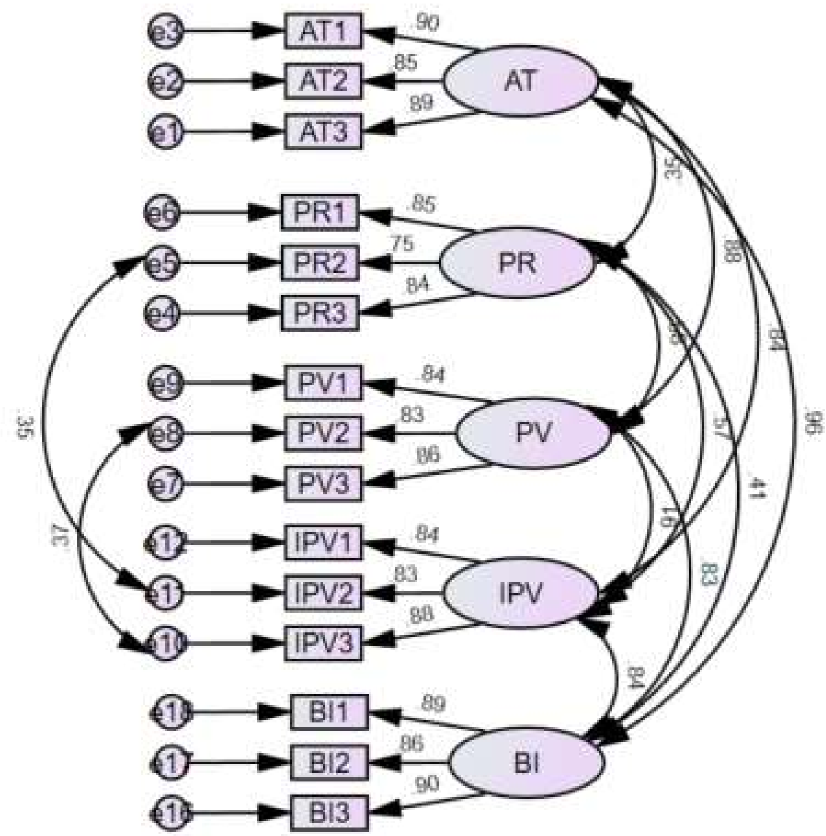


Figure 8

The Final Specified CFA Model



Reliability and Validity. Convergent validity and discriminant validity were examined for the final CFA model. Four indicators of convergent validity were evaluated, including factor loading, Construct Reliability (CR), Average Variance Extracted (AVE), and Maximum Shared Variance (MSV). The acceptance value for factor loading was ≥ .70, minimum .50, CR was ≥ .70, and AVE was ≥ .50 (Hair et al., 2010). All the standardized factor loadings passed the .70 threshold, and the CR values were greater than .70, indicating satisfactory consistency among items. AVE values for all factors were greater than .05, indicating satisfactory convergent validity. Table 7 shows the results of the convergent validity assessment for the final CFA model.

Table 7

Convergent Validity Assessment of the Final CFA Model

Construct	Item	Factor Loading	Squared multiple correlations	CR	Cronbach's alpha	AVE
Attitude	AT1	.90	.81	.91	.91	.77
	AT2	.85	.72			
	AT3	.89	.79			
Perceived Risk	PR1	.85	.72	.85	.85	.66
	PR2	.75	.56			
	PR3	.84	.70			
Perceived Value (Tangible)	PV1	.84	.71	.88	.88	.71
	PV2	.83	.69			
	PV3	.86	.74			
Perceived Value (Intangible)	IPV1	.84	.71	.89	.88	.72
	IPV2	.83	.69			
	IPV3	.88	.78			
Behavioral Intention	BI1	.89	.79	.92	.91	.78
	BI2	.86	.75			
	BI3	.90	.81			

Note. CR = Construct Reliability, AVE = Average Variance Extracted

Discriminant validity was tested by using the Fornell-Larcker method, which compared the AVE values to the squared correlation estimates of two constructs, as shown in Table 8. The correlation between AT and BI was slightly higher than the AVE value. AT passed the AVE test and failed the discriminant validity test, but it was reinstated in the model to avoid losing information. Table 8 shows the discriminant validity values.

Table 8

Discriminant Validity

	AT	PR	PV	IPV	BI
AT	.878				
PR	.126	.814			
PV	.774	.341	.844		
IPV	.712	.328	.819	.851	
BI	**.929**	.168	.691	.706	.884

Note. AT = Attitudes; PR = Perceived Risk; PV = Tangible Perceived Value; IPV = Intangible Perceived Value; BI = Behavioral Intentions.

Structural Model Assessment

The final CFA model in Figure 6 was transformed into an SEM model, as shown in Figure 7. The exogenous variables were attitude, perceived risk, perceived value of tangible items, and perceived value of intangible items. The endogenous variable was the behavioral intention to evacuate with carry-on baggage. The data were again assessed for normality and outliers. All kurtosis values were less than 5.00 and squared Mahalanobis values were less than 65.

Overall model fit. The same acceptance value was used to analyze the model fit. Two pairs of covariances were added between the largest values of error terms. As shown in Table 9, the overall model fit did not change from the CFA model. The revised SEM model indicated an acceptable model fit.

Table 9

Model Fit Comparison Between SEM Model and CFA Model

Model Fit Index	Structural Model	Measurement Model
X^2	231.780	231.780
df	78	78
Probability	***	***
GFI	**.878**	**.878**
NFI	.940	.940
CFI	.959	.959
CMIN/df	2.972	2.972
RMSEA	**.084**	**.084**

Note. *** significant at $p < .001$.

Hypothesis Testing. The hypotheses for the SEM model were:

H4: Attitudes are positively related to passengers' intentions to evacuate with carry-on baggage.

H5: Perceived risk is negatively related to passengers' intention to evacuate with carry-on baggage.

H6: Perceived value of tangible items is positively related to passengers' intention to evacuate with carry-on baggage.

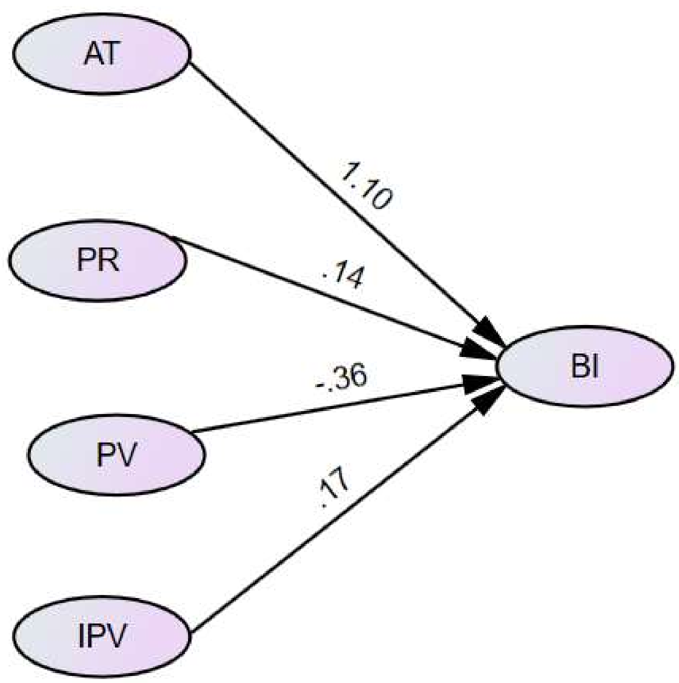
H7: Perceived value of intangible items is positively related to passengers' intention to evacuate with carry-on baggage.

H8: Awareness is negatively related to passengers' intention to evacuate with carry-on baggage.

The removal of construct AW meant it was unnecessary to hypothesis 8, awareness negatively influences behavioral intentions to evacuate with carry-on baggage. Thus, H_5 was removed. Figure 9 illustrates the standardized path coefficients for the SEM model. Table 10 shows the hypothesis testing results for the SEM model. H4 had the path estimates that were statistically significant in the expected direction. H5 and H6 had path estimates that were statistically significant but in the opposite direction. Therefore, H5 and H6 were not supported. H7 was not significant, therefore, not supported.

Figure 9

Standardized Path Coefficients for SEM Model



Note. AT = Attitude, PR = Perceived Risk, PV = Perceived Value (Tangible), IPV = Perceived Value (Intangible), BI = Behavioral Intention

Table 10

Structural Model Hypothesis Testing

Hypothesis	SRW	*t*-value	*p*-value	Result
H4: Attitudes → Behavioral Intentions	1.096	8.107	***	Supported
H5: Perceived Risk → Behavioral Intentions	0.139	2.292	.022	NS
H6: Perceived Value (Tangible) → Behavioral Intentions	-0.365	-2.218	.027	NS
H7: Perceived Value (Intangible) → Behavioral Intentions	0.166	1.496	.135	NS

Note. *** significant at $p < .001$. SRW = Standardized Regression Weights, NS = Not Supported

H4 proposed a positive relationship between passengers' attitudes and their intentions to evacuate with carry-on baggage. The hypothesis had a statistically significant value ($p < .001$); the estimate had significance above the critical t-value at the .05 level. Thus, H1 was supported, indicating that the more positive attitude passengers have towards evacuating with carry-on baggage, the more intention to evacuate with carry-on baggage. As AT increases by 1.0, BI will also increase by 1.096.

H5 predicted a negative relationship between perceived risk and passengers' intentions to evacuate with carry-on baggage. In fact, the standardized regression weight was positive (0.139), which was not in line with the hypothesized direction. The positive relationship was significant at $p = .022$ with a t-value greater than 1.96. Therefore, H5 was not supported.

H6 was not supported, indicating insufficient evidence to conclude that perceived value of tangible items has a positive influence on passengers' intentions to evacuate with carry-on baggage. In fact, the standardized regression weight was negative (-0.365), indicating the opposite effect. The negative relationship was significant at $p = .027$ with a t-value greater than 1.96.

H7 hypothesized a positive relationship between perceived value of the intangible items and passengers' intentions to evacuate with carry-on baggage. The relationship was not statistically significant ($p = .135$), therefore not supported. It showed that perceived value of the intangible items was not an important factor in passengers' intentions to evacuate with carry-on baggage.

Chapter Summary

Chapter IV presented the results for Study 1 and Study 2. Results for Study 1 showed baseline model validation and the results for the experimental model. A one independent-sample t-test was not significant, which validated the baseline model. A two-way ANOVA was conducted to examine the effects of the percentage of passengers evacuating with carry-on baggage and exit selection choice on evacuation time. The interaction effect was not significant. The main effect of the percentage of passengers evacuating with carry-on baggage was significant. The mean evacuation time for 0% was significantly lower than 50% and 80%. The main effect for the exit selection choice was also found significant; the mean evacuation time for the shortest queue choice was lower than the closest exit choice.

Results for Study 2 determined the factors that affect passengers' intentions to evacuate with carry-on baggage. A pilot study was conducted before the large-scale surveys. The sample size was reduced from 300 to 281 due to missing data. Descriptive statistics summarized the characteristics of the respondents. The CFA process was used to assess the measurement model. The initial model did not have the best model fit; therefore, model respecification was performed to remove the factor 'Awareness' and add covariances to the two largest error terms to improve the final model and achieve an acceptable model fit. The CFA model met the convergent and discriminant validity tests with the exception of the factor AT. However, as AT passed the AVE test, the model overall achieved an acceptable construct validity.

The SEM was used to assess the structural model, which showed an acceptable model fit. The hypothesis testing showed that H4 was supported, while H5, H6, and H7 were not supported. Chapter V discussed the results of the study in theoretical and research contexts. Conclusions were drawn, and recommendations for future research were proposed.

Chapter V: Discussion, Conclusions, and Recommendations

This study investigated the effect of carry-on baggage on aircraft evacuation efficiency using an agent-based simulation model and assessed the factors that influence passengers' intention to evacuate with carry-on baggage through the SEM model. The results are discussed in this chapter for possible reasons for the findings with conclusions. This chapter also includes recommendations for future research.

Discussion of Study 1 Results

Baseline Model Validation

It was impossible to gather real-life data of aircraft evacuations from A380, so the evacuation drill data were used for the baseline model validation. Aircraft manufacturers are required to conduct an emergency evacuation demonstration as realistic as possible. The real-life evacuation drill was carried out in 2006 under the supervision of Airbus, FAA, and the European Aviation Safety Agency. Data were retrieved from the video taken during the evacuation drill that was uploaded on YouTube.

Control variables such as the type of the aircraft, number and location of the exits, and the exit selection choice for the simulation were consistent with the evacuation drill. Also, both the baseline model and actual evacuation drill used A380 and the flight crew guided the passengers to the exit with the shortest queue.

The baseline model validation results showed no significant difference between the baseline model of the simulation and the actual data from the real-life evacuation drill. Therefore, the baseline model validation results suggested that the baseline model was validated to produce similar statistical results as the real-life evacuation drill.

However, it is crucial to acknowledge that the accuracy of the baseline model would also depend on the representation of human behaviors. Although the social force model was implemented to simulate passengers' moving speed based on Newtonian mechanics, various human behavior under panic and the decision-making process was not included in the simulation model. As discussed in Chapter II, the social force model can realistically describe pedestrian behavior under non-panic evacuations (Li et al., 2014). Besides, participants in the evacuation drill were aware of the situation and knew that their lives were not in danger. Therefore, both the evacuation drill and the baseline simulation could not implement real-life panic behavior.

The level of panic could vary depending on the remaining time to evacuate from the situation, waiting time for the exits, and the difficulty to find the exit (Miyoshi et al., 2012). Therefore, the level of panic would be different for each evacuation situation. Li et al. (2014) supported that panic behavior could increase the overall evacuation efficiency with 1800 or fewer evacuees. However, Wang et al. (2015) found that panic behavior could decrease evacuation efficiency due to crowded evacuees. Both Li et al. (2014) and Wang et al. (2015) agreed that the number of casualties increased with panic behavior.

Experiment Model Results

The experiment model results suggested three outcomes: (1) Evacuation efficiency would decrease if 50% or more passengers evacuate with carry-on baggage compared to no passenger evacuating with carry-on baggage, (2) Evacuation efficiency would increase when crew members guide the passengers to the exit with the shortest queue compared to passengers choosing the closest exit to evacuate, and (3) There is no interaction effect between the percentage of passengers evacuating with carry-on baggage and exit selection choices.

Percentage of Passengers. The results indicated that the evacuation time takes significantly longer when 50% or 80% of passengers evacuate with carry-on baggage compared to 0% of passengers evacuating with carry-on baggage. The effect size of partial η^2 was .126, which suggested a strong effect of a difference in the total evacuation time. Therefore, the results would suggest that the evacuation efficiency would significantly decrease when 50% or more passengers evacuate with carry-on baggage. However, the evacuation efficiency did not significantly differ between 50% and 80% of the passengers evacuating with carry-on baggage. Therefore, evacuation efficiency would decrease once passengers with carry-on baggage exceed 50% of the passengers.

One possible explanation is that the total evacuation time would significantly increase with a larger number of passengers with carry-on baggage, but only up to a point. The effect of the percentage of passengers with carry-on baggage could not be linear. The outcome could have reached the maximum value at 50%. Therefore, the effect of carry-on baggage on evacuation efficiency would not significantly increase when the number of passengers increased to a certain point (in our study, 50%).

Exit Selection Choices. The results revealed that the evacuation efficiency would significantly increase when passengers use the exit with the shortest queue compared to the closest exit. The effect size of partial η^2 was .968, which suggested a powerful effect of a difference in the total evacuation time. Passengers could choose the exit with the shortest queue from crew members' guidance or actively search for an alternative escape route.

Failure to evacuate from an aircraft promptly could lead to injury and even affect the passengers and crew members' survivability. According to the FAA (2004), all passengers, including crewmembers at full seating capacity, should evacuate within 90 seconds or less at emergencies. The FAA suggested 90-second as the maximum amount of time before toxic fumes and flames overcome the cabin with fire. Moreover, flashover may occur before the evacuation is complete. Flashover refers to the near-simultaneous ignition of all combustible material within an enclosed area (Skybrary, 2019). Therefore, any number above 90 seconds could indicate a tragedy with increased damages.

The researcher counted the frequency of the total evacuation time that exceeded 90 seconds. The results of the current study revealed that the frequency of the total evacuation time exceeding 90 seconds increased when the percentage of passengers with carry-on baggage was set as 80%. With the shortest queue choice, all evacuation times for 0% and 50% did not exceed 90 seconds. However, five out of 50 total evacuation times exceeded 90 seconds when 80% of the passengers evacuated with carry-on baggage. Thus, a higher percentage of passengers evacuating with carry-on baggage from 50% to 80% would not necessarily mean that the average total evacuation time would be higher. However, the possibility of getting a longer evacuation time above 90 seconds would increase.

Moreover, the findings indicated that 100% of the total evacuation time exceeded 90 seconds when the closest exit choice was used. The mean evacuation time for shortest queue choice (*M* = 80.75, *SD* = 4.35) was lower than 90 seconds, whereas the mean evacuation time for the closest exit choice (*M* = 118.98, *SD* = 3.06) exceeded 90 seconds.

However, TSB (2013) found that passengers tend to be fixated on a specific exit and did not actively look for an alternative exit. Passengers often tried to use the aircraft's exit from the same door they entered, even though there were better options with less queue. For instance, in an evacuation at Calgary, passengers in the first seven rows of the aircraft chose the left front exit, which was the same door that they entered, although the right front exit was visible, open, and manned by a flight crew (TSB, 2013). Therefore, a crew member had to stand in the middle of the two exits and forcefully direct the passengers to the right exit. Moreover, behaviors were often observed where passengers continued to stand in a queue to use an exit even though the other forward exits were completely free to use (TSB, 2013). As the findings from the current study suggested that the shortest queue choice increases evacuation efficiency, passengers should actively look around for an alternative exit with a shorter queue to reduce the total evacuation time.

Discussion of Study 2 Results

This study examined the behavioral intention of passengers to evacuate with carry-on baggage. The TPB was employed to provide a theoretical basis for the framework. Four hypotheses were tested.

Passenger Characteristics

This study used a non-probability convenience sampling method to collect data from 300 participants, but the final sample size of viable data was 281 due to data cleaning. There were more male participants (64.4%) than female participants (35.6%), and the respondents were mostly aged 20 – 30 years (65.8%) with Bachelor's degree (63.3%). The majority of the participants were employed full-time (91.1%), and the participants were mostly from North America (43.4%) or Asia (41.3%). MTurk workers tend to be Internet users in the eLancing work environment and tend to be younger than the general population (Cheung et al., 2017). Whites and Asians were also overrepresented, whereas Blacks and Hispanics tend to be underrepresented on MTurk compared to the general population (Cheung et al., 2017).

Model Modifications and Results

The original CFA model contained five predicting variables – attitude (AT), perceived risk (PR), perceived value of tangible products (PV), perceived value of intangible products (IPV), and awareness (AW). The outcome variable was passengers' behavioral intentions to evacuate with carry-on baggage at an emergency (BI). However, the model fit indices of the initial model for GFI, CMIN/*df*, and RMSEA and the validity showed unacceptable values. Therefore, changes were made to improve the model fit and validity. AW was removed due to high discriminant validity. A covariance between BI and AW was observed; the discriminant validity results suggested a high correlation between the two factors. Therefore, the AW factor was removed to improve the discriminant validity. Two error covariances were also created between error terms from the largest MI values.

The final CFA model included four predicting variables – AT, PR, PV, and IPV. The model fit indices of the final CFA model showed improvement within an acceptable threshold. All results for the convergent validity assessment showed a satisfactory result without exceptions. The factor AT did not pass the discriminant validity test, but the factor had a high AVE score of .77. Therefore, the factor AT was reinstated in the model to avoid losing information.

Of the four hypotheses, only H4 was supported, while H5, H6, and H7 were not supported. A detailed discussion of the individual hypotheses follows in the next subsection.

Attitudes. In terms of aircraft evacuation, attitude represents favorable or unfavorable opinion toward the behavior of evacuating with carry-on baggage (Ajzen, 2002a). Chapter IV suggested that attitudes had a strong positive influence on passengers' behavioral intentions to evacuate with carry-on baggage. In other words, passengers with favorable opinion toward the behavior of evacuating with carry-on baggage would have the intention to evacuate with carry-on baggage. This finding was expected as it was one of the fundamental relationships of the TPB. The TPB supported that stronger attitudes towards a behavior lead to a stronger intention to perform the behavior (Ajzen, 2002a).

The relationship between attitude and intention was also supported by numerous researchers (Bashir et al., 2019; Morosan, 2012; Pan &Truong, 2018; Zhang et al., 2019). For instance, Morosan (2012) supported that attitude towards registered traveler biometric systems was the most significant factor in their intentions to use the biometric systems. However, the effects of attitude on behavioral intentions in evacuation situations have not been fully researched. Therefore, this finding is crucial as it provided empirical evidence of the positive relationship between attitudes and passengers' intentions in evacuation situations.

The standardized regression weight between attitudes and behavioral intention indicated a potentially high value of 1.10. Therefore, the results indicate a strong correlation between the factors.

Perceived Risk. In the aircraft evacuation context, perceived risk is how the evacuees feel “at-risk” in the evacuation (Kuligowski, 2011). The researcher expected to find a significant negative relationship for perceived risk, supported by the literature review. For instance, pedestrians with lower perceived risk took longer pre-evacuation delays (Sherman et al., 2011). However, the results of the current study indicated that the hypothesis was not supported. In fact, the results suggested the opposite effect, where the positive relationship was significant. As passengers perceive a greater risk, they are more likely to have the intention to evacuate with carry-on baggage.

The findings could be explained that the passengers with more perceived risk lead to an increased intention to keep their carry-on bags to protect themselves. For instance, passengers could think that there is no opportunity to get the baggage back if the situation is more dangerous. However, passengers could think that the probability of getting their baggage back would increase if the situation is less dangerous, reducing the risk of losing the items in the carry-on baggage.

Herjanto et al. (2021) suggested that perceived risk and situational ambiguity is responsible for panic buying. Panic buying has been a huge problem during the COVID-19 pandemic, where customers purchased a large number of products to reduce the probability of future shortage (Herjanto et al., 2021). An aircraft emergency evacuation can be compared to the COVID-19 pandemic, as passengers cannot easily recognize or understand their current situation. Therefore, passengers would experience a high level of uncertainty and unpredictable consequences (Bruwer et al., 2013). Herjanto et al. (2021) also supported that empty shelves and long queues at grocery stores represented a risky situation, which roused customers to panic buying. In terms of aircraft evacuation, opened overhead compartments and queues at the exits would represent a risky situation, which could affect other passengers to retrieve their baggage as well.

Perceived Value. The results indicated that there was insufficient evidence to conclude PV influences BI. Again, the researcher expected to find a significant positive relationship for perceived value of tangible products, but the results suggested the opposite effect, where the negative relationship was significant. As passengers perceive a higher tangible value of their baggage, they are less likely to have the intention to evacuate with carry-on baggage. There was no obvious explanation for this result.

The results also indicated that there was insufficient evidence to conclude IPV influences BI. The relationship was not statistically significant, therefore, not supported. The insignificant effect of perceived value revealed in this study provided a new understanding of perceived value of carry-on baggage in aircraft evacuations. In an emergency, passengers may not recall the exact items in their carry-on baggage in the overhead compartment. What is in the baggage may not matter for the passengers to retrieve their carry-on baggage.

Conclusions

The purpose of this research was to investigate the effect of carry-on baggage and exit selection choice on aircraft evacuation efficiency and determine the factors that influence the passengers' intention to evacuate with carry-on baggage under the emergency landing. Results showed that the percentage of passengers evacuating with carry-on baggage and exit selection choices significantly affected the total evacuation time. The critical result of Study 1 implied that more passengers evacuating with carry-on baggage and closest exit choice could decrease the evacuation efficiency and even affect the survivability of the passengers.

The theoretical model for Study 2 was developed based on the TPB, with external factors added to reflect the context of aircraft evacuation. An online survey was used to collect data from MTurk. A SEM approach was used to analyze the data. The key results of Study 2 highlighted that attitude positively affect the intentions to evacuate with carry-on baggage. The current study makes significant theoretical and practical contributions as the first study to investigate the factors of behavioral intentions of passengers to evacuate with carry-on baggage in the context of aircraft evacuation.

Theoretical Contributions

The results of this study contribute to the literature in several ways. First, the study contributes to the body of knowledge regarding carry-on baggage at an aircraft emergency. The simulation model demonstrated that the effect of carry-on baggage could be implemented on simulations with proper parameters. The validated baseline simulation model can be further applied to investigate other factors such as waiting time for exits, evacuation with children, people with disabilities etc. The SEM model validated that established factors of the TPB may be expanded and applied to aircraft evacuations and human behavior at aircraft evacuations. The SEM model with the extended TPB model can be further applied to other factors for a comprehensive understanding of passengers' behavioral intentions to evacuate with carry-on baggage.

Second, the model showed the use of TPB and SEM in the context of aircraft emergency studies. Moreover, the model further proposed PR and PV as factors that may be utilized to assess the behavioral intentions to evacuate with carry-on baggage. So far, TPB has been adapted and validated to examine many fields such as customers' behavioral intentions, yet the evacuation behaviors and aircraft evacuation were not researched. Also, extensive studies on aircraft evacuation have paid less attention to the passengers' evacuating behavior with carry-on baggage. Thus, the study fills a gap of studies in aircraft evacuation to provide a more comprehensive understanding of the factors that affect passengers' behavioral intentions to evacuate with carry-on baggage, and the effect of carry-on baggage on the overall evacuation efficiency.

Practical Contributions

The study took measures to increase the generalizability of the study. The results of the study can have important practical contributions for several parties, including the FAA, NTSB, airlines, and professionals in the field.

First, this study responds to the NTSB as they asked the FAA to "measure and evaluate the effects of carry-on baggage on passenger deplaning times and safety during an emergency evacuation" (NTSB, 2018, p. 66). The results of this study provide solid quantitative evidence of the effects of carry-on baggage on passenger deplaning times. The NTSB (2000) also reported that nearly 50% of passengers with carry-on bags admitted that they tried to take their bags during the aircraft evacuations, and most passengers actually exited with their bags. The results from the current study suggested that 50% of passengers evacuating with carry-on baggage would significantly reduce the evacuation efficiency. Therefore, evacuation efficiency would have been significantly reduced at most aircraft evacuations, which can be translated to possible loss of lives under emergency situations.

The second practical contribution comes from the effect of attitude on passengers' intention to evacuate with carry-on baggage. Government agencies, airlines, and other stakeholders should promote safety-first behavior and educate the passengers by showing the consequences of evacuating with carry-on baggage and support with compensations for lost bags to reduce the positive attitude towards evacuating with carry-on bags.

Third, the findings can provide airlines with a better understanding of factors under aircraft emergency landing. The industry and other stakeholders can also understand the effect of these factors that influence passengers to evacuate with carry-on baggage. For Study 1, as the effects of evacuating with carry-on baggage on evacuation efficiency have been found, the findings should be utilized to promote safety increase the survivability of the passengers by ensuring policies. There should be strict enforcement prohibiting passengers from retrieving their belongings during an aircraft evacuation to maximize the survivability of the passengers.

For Study 2, as research into factors influencing passengers' evacuating with carry-on baggage continues, the FAA and other stakeholders may use the findings of the study beneficial to make better policies to improve evacuation efficiency.

Finally, this study can be adapted for use by other studies. The survey methodology may provide insight into passengers' intention to evacuate from aircraft concerning other human behaviors. It is believed that this study serves as a pioneering groundwork for greater recognition and examination into carry-on baggage under emergency evacuations.

Limitations of the Findings

There are some limitations to this study. Although the limitations could constrain the study results, the importance of the findings would not be diminished. First, limitations could exist in the simulation model as the data were not collected through an experiment and used a generic model. Therefore, many assumptions were made, including passengers' decision-making and the exit selection choices, which would be different from real-world situations. The natural human behavior of an aircraft evacuation, such as panic behavior was not simulated in the study.

Third, limitations may exist in terms of the representativeness of the survey results for Study 2. SEM requires a large sample size, but the sample size was limited due to time and budget constraints. Initially, 300 responses were gathered through an online survey, but data cleaning reduced it to 281. Moreover, the non-probability convenience sampling method could influence its ability to represent the population.

Recommendations

Based on the discussion of the finding, theoretical and practical contribution, and limitations of the findings, three recommendations were proposed to (1) guide future research and (2) help policymakers and the industry.

For Study 1, researchers should consider other factors that can affect aircraft evacuation efficiency. For example, factors such as the waiting time for the exits, other types of aircraft considering narrow-body aircraft and wide-body aircraft, size of the luggage, and evacuation with children can be considered to improve the simulation model's validity. In addition, collecting these data through experiments would fine-tune the model.

For Study 2, future researchers should consider other factors that can affect the behavioral intentions to evacuate with carry-on baggage. For example, the education level, the purpose of the trip, and cultural background can be considered to expand the understanding of the behavior. Factors from the original TPB, such as the perceived behavioral control and subjective norms, should also be considered for future researchers. Besides, the SEM model should be more comprehensive. For instance, increased sample size and random sampling method are recommended for future research. The random sampling method would help generalize the findings of the research.

In conclusion, this study laid out a fundamental basis for carry-on baggage in aircraft emergencies. The results of the study fill a gap in the research of aircraft emergency evacuation, and the models may be adapted for other factors that affect aircraft evacuations. It is believed that the research on aircraft emergency evacuations can help reduce the casualties and increase survivability. Study on the factors that affect aircraft evacuations will improve the cabin's safety through better training and emergency procedures.

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Appendix A

Permission to Conduct Research

Embry-Riddle Aeronautical University
Application for IRB Approval
EXEMPT Determination Form

Principal Investigator: Sang-A Lee

Other Investigators: Dr. Dahai Liu

Role: Student **Campus:** Daytona Beach **College:** Aviation/Aeronautics

Project Title: Effect of Carry-on Baggage on Evacuation Efficiency

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 12/04/2020 **Approval #:** 21-047

Determination: Exempt

Dr. Beth Blickensderfer
IRB Chair Signature: Elizabeth L. Blickensderfer, Ph.D. Digitally signed by Elizabeth L. Blickensderfer, Ph.D. Date: 2020.12.11 11:04:05 -05'00'

Brief Description:

The purpose of this study is to determine the factors influencing passengers' intention to evacuate an aircraft with carry-on baggage from an aircraft. Participants will be asked to complete a survey through Amazon Mechanical Turk.

This research falls under the **EXEMPT** category as per 45 CFR 46.104:

☑ (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: (Applies to Subpart B [Pregnant Women, Human Fetuses and Neonates] and does not apply for Subpart C [Prisoners] except for research aimed at involving a broader subject population that only incidentally includes prisoners.)

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4 December 2020

Human Subject Protocol Application

Campus:	**Daytona Beach**	College:	**Other**
Applicant:	**Sang-A Lee**	Degree Level:	**Master**
ERAU ID:		ERAU Affiliation:	**Student**

Project Title: **Effect of Carry-on Baggage on Evacuation Efficiency**

Principal Investigator: **Sang-A Lee**

Other Investigators: **Research advisor: Dr. Dahai Liu**

Submission Date: **11/14/2020**

Beginning Date: **01/27/2021**

Type of Project: **Survey**

Type of Funding Support (if any): **College Philanthropy Councils**

Questions:

1. Background and Purpose: Briefly describe the background and purpose of the research.

   The most frequent obstacle of an aircraft evacuation is the passengers carrying baggage while evacuating. For instance, passengers' evacuating behavior with carry-on baggage was observed in recent accidents, including Aeroflot flight 1492, which led to 41 fatalities. Therefore, the purpose of this study is to determine the factors influencing passengers' intention to evacuate with carry-on baggage from an aircraft.

2. Time: Approximately how much time will be required of each participant?

   Approximately 10 minutes will be required.

3. Design, Procedures and Methods: Describe the details of the procedure(s) to be used and the type of data that will be collected.

   This study will follow a quantitative research method with a cross-sectional, survey design. The survey will be conducted online through the Amazon Mechanical Turk (MTurk) website. MTurk is a widely used online survey tool by behavioral researchers to recruit research participants. This study will employ a structural equation modeling (SEM) method.

4. Measures and Observations: What measures or observations will be taken in the study?

The questionnaire will be used as the research instrument. The questionnaire will be divided into three sections. The first section will ask the filter questions – Have you ever traveled with an airline before? and Are you eighteen years or older? These dichotomous filter questions will test the eligibility of the participants, so participants who are eighteen years or older and who have flown with an airline before will be eligible to participate in the survey.
The second section will ask the passengers' demographics, including age, gender, education level, monthly income, occupation, and nationality.
The third section will include questions concerning passengers' awareness and assess the factors that may influence passengers' intentions to evacuate with carry-on baggage. Seven Likert-type scale items will be used to measure the factors.

5. Participant Population and Recruitment Procedures: Who will be recruited to be participants and how will they be recruited. Any recruitment email, flyer or document(s) must be reviewed by the IRB. Note that except for anonymous surveys, participants must be at least 18 years of age to participate.

Approximately 200 participants will be required for this study. Participants need to be 18 years of age or older and have traveled with an airline before. They will be acquired using Amazon Mechanical Turk (MTurk), an online research tool. Amazon MTurk allows participants to participate in studies to acquire credit. Researchers list studies on MTurk with information about the research, and the credits that can be earned from participating. Participants can choose what study to participate in.

6. Risks or Discomforts: Describe any potential risks to the dignity, rights, health or welfare of the human subjects. All other possible options should be examined to minimize any risks to the participants.

The risks of participating in this study are minimal, no more than what is experienced in everyday life.

7. Benefits: Assess the potential benefits to be gained by the subjects as well as to society in general as a result of this project.

While there is no benefit to the participant in this study, their participation will promote the understanding of factors influencing passengers' intentions in an aircraft evacuation.

8. Informed Consent: Describe the procedure you will use to obtain informed consent of the subjects. How and where will you obtain consent? See Informed Consent Guidelines for more information on Informed Consent requirements.

The informed consent form will be presented to participants at the beginning of the online survey. Participants will indicate they have read the form and agree to participate by selecting 'yes' on the question - Do you agree to the informed consent provided? Those who do not consent to the study will not continue to participate.

9. Confidentiality of Records: Will participant information be anonymous (not even the researcher can match data with names), confidential (Names or any other identifying demographics can be matched, but only members of the research team will have access to that information. Publication of the data will not include any identifying information.), or public (Names and data will be matched and individuals outside of the research team will have either direct or indirect access. Publication of the data will allow either directly or indirectly, identification of the participants.)?

Anonymous

9b. Justify the classification and describe how privacy will be ensured/protected.

All data will remain anonymous, and no names will be associated with any data resulting from this study. No one other than the researcher will have access to any of the responses. All survey responses that the investigator receives will be treated confidentially and stored in a password-protected file on a password-protected computer.

10. Privacy: Describe the safeguards (including confidentiality safeguards) you will use to minimize risks. **Indicate what will happen to data collected from participants that choose to "opt out" during the research process.** If video/audio recordings are part of the research, describe how long that data will be stored and when it will be destroyed.

Individual information will be protected in all data resulting from this study. No personal information will be collected other than basic demographic descriptors. The online survey system will not save IP addresses or other identifying information. No data will be collected from participants who choose to 'opt out' during the research process; their data will be destroyed.

11. Economic Considerations: Are participants going to be paid for their participation?

Yes

11b. What will the compensation be?
Describe your policy for dealing with participants who 1) Show up for research, but refuse informed consent; 2) Start but fail to complete research.

Participants will be paid $1.00 for their participation. Those who do not sign the informed consent form will not be compensated. Those who start the survey, but do not complete the survey will still be compensated.

By submitting this application, you are signing that the Principal Investigator and any other investigators certify the following:
1. The information in this application is accurate and complete
2. All procedures performed during this project will be conducted by individuals legally and responsibly entitled to do so
3. I/we will comply with all federal, state, and institutional policies and procedures to protect human subjects in research
4. I/we will assure that the consent process and research procedures as described herein are followed with every participant in the research
5. That any significant systematic deviation from the submitted protocol (for example, a change in the principal investigator, sponsorship, research purposes, participant recruitment procedures, research methodology, risks and benefits, or consent procedures) will be submitted to the IRB for approval prior to its implementation
6. I/we will promptly report any adverse events to the IRB

Electronic Signature:

Sang-A Lee

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16 December 2020

Modification of Previously Approved IRB

Campus:	**Daytona Beach**	College:	**COA**
Applicant:	**Sang-A Lee**	Degree Level:	**Master**
ERAU ID:	**2488528**	ERAU Affiliation:	**Student**
IRB Approval Number:	**21-047**		
Project Title:	**Effect of Carry-on Baggage on Evacuation Efficiency**		
Principal Investigator:	**Sang-A Lee**		
Other Investigators:	**Dr. Dahai Liu is the Committee Chair.**		

Approval of Modification of Already Approved IRB:

☒ Validated as continuing to meet the criteria for Exempt or Expedited status.

Submission Date: **12/15/2020**

Beginning Date: **12/29/2020**

Type of Funding Support (if any):

Beth Blickensderfer, PhD — December 16, 2020

Signature of IRB Chair — Modification Approval Date

Questions:

1. Change of Protocol due to change in:

   Participant population

1b. Please summarize:

   We would like to increase the number of participants from 200 to approximately 300.

   By receiving comments from subject matter experts, the participant number should be increased to 300 as Structural Equation Modeling (SEM) requires a large number of participants and to increase the power of the study. The compensation will remain the same for each participant.

   Also, to accommodate the comments received with the approval, the survey will specify the carry-on baggage as 'any baggage that is stored in the overhead compartments or underneath the seat'. This information will be given to the survey participants in the survey scenario section.

   The informed consent form will remain the same.

2. Have you started the recruitment process?

   No

3. Have you received any complaints or experienced unanticipated problems with this project?

No

Appendix B

Data Collection Device

INFORMED CONSENT FORM

Survey of the Effect of Carry-on Baggage on Evacuation Efficiency

Purpose of this Research: I am asking you to take part in this research project for the purpose of learning passengers' viewpoints related to emergency evacuation and the factors influencing their intentions to evacuate with carry-on baggage in an aircraft. During this study, you will be asked to complete a brief online survey about your opinions concerning the aircraft evacuation with carry-on baggage. The completion of the survey will take approximately ten minutes.

Eligibility: To participate in this study, you must be 18 years or older, and have travelled with an airline before.

Risk or discomforts: The risks of participating in this study are minimal, no more than what is experienced in everyday life.

Benefits: While there is no benefit to you as a participant in this study, your participation will promote the understanding of factors influencing passengers' intentions in aircraft evacuation.

Confidentiality of records: Your individual information will be protected in all data resulting from this study. Your responses to this study will be anonymous and no name will be associated with any participant's data. No personal information will be collected other than basic demographic descriptors. The online survey system will not save the IP addresses. No one other than the researcher will have access to any of the responses. All survey responses that the investigator receives will be treated confidentially and stored in a password-protected file on a password-protected computer. However, given that the surveys can be completed from any computer (personal, work, school, etc.) we are unable to guarantee the security of the computer on which you choose to enter your response. As a participant in this study, the investigator wants you to be aware that certain "keylogging" software programs exist that can be used to track or capture data that you enter and/or websites that you visit. Information collected as part of this research will not be used or distributed for future research studies.

Compensation: By participating in this survey, you will receive $1.00 through Amazon MTurk.

Contact: If you have any questions or would like additional information about this study, please contact Sang-A Lee, lees98@my.erau.edu, or the faculty member overseeing this project, Dr. D. Liu, liu89b@erau.edu. For any concerns or questions as a participant in this research, contact the Institutional Review Board at 386-336-7179 or via email teri.gabriel@erau.edu.

Voluntary Participation: Your participation in the survey is completely voluntary. You may discontinue your participation at any time without penalty or loss of benefits to which you are otherwise entitled. Should you wish to discontinue the research at any time, no information collected will be used.

CONSENT. By checking AGREE in the first section of the survey, I certify that I am 18 years or older, have travelled with an airline before, and voluntarily agree to participate in the study.

If you do **not** wish to participate in the study, simply check disagree in the question and close the browser.

Please print a copy of this form for your records. A copy of this form can also be requested from Sang-A Lee, lees98@my.erau.edu

Scenario: Imagine that you are in a given scenario where there is a fire onboard the aircraft, indicated by smoke in the cabin. Only 50% of the exits will be available. The "carry-on baggage" refers to any item that you store in the overhead compartments or underneath the seat in front of you.

Section 1. Filter Questions (yes/no)

1.1 Have you ever travelled with an airline before?
1.2 Are you eighteen years or older?
1.3 Do you agree to the informed consent provided?

Section 2. Demographics

2.1 Gender (Male, female)
2.2 Age (20 or younger, 21-30 years, 31-40 years, 41-50 years, 51-60 years, 60 or older)
2.3 Education level (Lower than High school, High school, bachelor’s degree, master’s degree, higher than master’s degree)
2.4 Monthly income in USD (0 – 500, 501 – 1000, 1001 – 1500, 1501 – 2000, 2001 – 2500, 2501 and above)
2.5 Occupation (Student, full-time employment, part-time employment, unemployed, other)
2.6 Nationality (North America, South America, Europe, Asia, Africa, Antarctica, Australia)

Section 3. Factors affecting passengers’ intentions to evacuate with carry-on baggage (1: Strongly agree, 5: Strongly disagree)

AT1. Evacuating with carry-on baggage in the given scenario would be wise.
AT2. Evacuating with carry-on baggage in the scenario would make me feel comfortable.
AT3. Evacuating with carry-on baggage in the scenario will be beneficial to me.
PR1. If I evacuate with carry-on baggage in the given scenario, I will endanger my life.
PR2. I will get seriously injured if I evacuate with carry-on baggage in the scenario.
PR3. Evacuating with carry-on baggage in the scenario is more dangerous than evacuating without carry-on baggage.
PV1. Tangible products in my carry-on baggage are precious.
PV2. Tangible products in my carry-on baggage are valuable.
PV3. Tangible products in my carry-on baggage are important.
PV4. Intangible products in my carry-on baggage are precious.
PV5. Intangible products in my carry-on baggage are valuable.
PV6. Intangible products in my carry-on baggage are important.
AW1. I know that evacuating with carry-on baggage is prevented by cabin crew.
AW2. I know that evacuating with carry-on baggage could endanger other passengers’ lives.
AW3. I know that evacuating with carry-on baggage would delay the evacuation process.

Section 4. Behavioral intention (1: Strongly agree, 5: Strongly disagree)

BI1. I would evacuate with carry-on baggage as described in the scenario.
BI2. If I encounter this situation in the future, I will evacuate with carry-on baggage
BI3. I would seriously consider evacuating with carry-on baggage in the scenario.