AMERICAN UNIVERSITY OF BEIRUT

EVACUATION BEHAVIOR IN RESPONSE TO HUMAN-MADE DISASTER IN BEIRUT CITY

by
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A thesis
submitted in partial fulfillment of the requirements
for the degree of Master of Engineering
to the Department of Civil and Environmental Engineering
of Maroun Semaan Faculty of Engineering and Architecture
at the American University of Beirut

Beirut, Lebanon
April 2022

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Acknowledgements

I would like to express my gratitude to Dr. Harith Abdulsattar and Dr. Maya Abou-Zeid for their guidance and tireless dedication to this study and my education. I would also like to express my gratitude to Dr. Issam Srour, my thesis committee member, for his time, comments, and dedication to this thesis. I would also like to acknowledge Maher Said for providing me with important information on structural equation modeling and his comments on the modeling part. Also, I would like to express my gratitude to the civil and environmental engineering department at the American University of Beirut for funding my graduate studies. Finally, I would like to thank my family and friends for supporting me to accomplish my dreams.

Abstract

of the Thesis of

Ghina Hasan Tahesh for Master of Engineering
Major: Civil and Environmental Engineering

Title: Evacuation Behavior in Response To Human-Made Disaster in Beirut City

Natural hazards and human-made threats are pressing issues in many urban areas. In general, natural and manmade disasters can be categorized into two main categories based on their lead warning times. The first type is a disaster with a long lead warning time, such as a hurricane, wildfire, or a far-field tsunami. The Second is disasters with a short-lead warning time, such as building fires, earthquakes, or human-made terrorist attacks. Evacuation plans for disasters with a long lead warning time can be made as soon as they are foreseen. However, no such preparation opportunity exists for disasters with less lead time due to their unexpected nature.

Human behavior impacts the evacuation process. Thus, studying human behavior in emergencies is vital for evacuation planning. This study aims to provide a comprehensive understanding of the decision-making process of residents in case a human-made disaster occurs with an application to Beirut, Lebanon.

This study is important for pre-disaster planning, which mitigates potential damage from such disasters. Using structural equation modeling (SEM), the current study uses the Protective Action Decision Model (PADM) framework to explain intention toward evacuation behavior before a human-made disaster in three situations: being at home with all family members, having absent family members, and being at work or university when the event occurs.

The findings of this study show that the PADM framework is relevant to explaining evacuation behavior intentions prior to a human-made disaster incident. The Main insights that apply to the three models are that cognitive factors like risk perception and knowledge perception are important determinants of evacuation behavior. Also, demographic characteristics and hazard cues influence evacuation behavior. Key results indicate that knowledge perception does not trigger the intended behavior of evacuating immediately in the three studied situations. Besides, the results indicate low confidence in the government's emergency plans and the unreliability of the official government warnings about human-made hazards.

Overall, the findings of this study may contribute to a better understanding of evacuation behavior from disasters with less lead warning time. Besides, they may aid the Disaster Risk Management unit of Lebanon in developing emergency evacuation strategies that: understand the public's evacuation behavior; customize city-specific evacuation logistics; optimize the dissemination of evacuation information.

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Chapter 1

Introduction

Natural and human-made hazards continuously threaten populations around the world. Natural hazards such as floods, hurricanes, wildfires, earthquakes, tsunamis, tropical cyclones, and tornadoes are caused by the movements of the Earth's crustal plates and climate change. On the other hand, human-made hazards include fires, car accidents, industrial accidents, oil spills, nuclear explosions or radiation, and terrorist attacks. Natural and human-made hazards can be a source of threat to people's lives and livelihoods; therefore, emergency evacuation is essential to move people away from the area where there is a possible threat to human lives and properties.

1.1 Motivation and Research Problem

Successful evacuation is highly dependent on several factors, such as warning time, response time, information and instructions dissemination procedure, evacuation routes, traffic flow conditions, and dynamic traffic control measures [3, 4]. During an evacuation, the response time is dependent on the nature of the hazard and an individual's perception of risk. In general, evacuation from disasters with long enough lead warning time (from hours to days) such as a hurricane, wildfire, or a far-field tsunami is usually more efficient in comparison to disasters with much less lead warning time, such as building fire, earthquakes, or human-made terrorist attacks where efficient and dynamic evacuation is crucial.

As the chance of survival depends on individuals' access to the surrounding facilities [5], well-prepared disaster management plans, effective protective actions, and systematic recovery operations have been generally thought to be the most significant in reducing heavy losses in disasters [6]. A disaster management system is defined as *"The execution of plans, the use of staff and equipment to meet the tactical and task requirements of responding to a given threat"* [7]. Transportation is a system in which its multi-layers intervene and interact with each other. The system is mainly driven by heterogeneity in human behavior resulting in an unpredictable and often unreliable performance of the system. Transportation network accessibility and proper evacuation plans are essential components of disaster management. The evacuation plan's efficiency is a crucial element toward the success of the evacuation of large urban areas.

Historically, emergency evacuation occurred in a chaotic way due to a rapid rise in traffic demand which often leads to congestion, driver anxiety, driver aggression, stress, and tiredness experienced by evacuees [8, 9, 10]. The lack of real-time information resulting from infrastructure damage and the increasing demand for the communication network can significantly aggravate the complexity of the evacuation process.

The evacuation process in highly populated areas due to natural or human-made disasters is a challenge still being confronted. Previous research on evacuation planning mainly focused on infrastructure-related issues such as traffic network capacity [11, 12]. However, efficient evacuation modeling requires the integration of natural, engineering, and social systems [13]. Therefore, less is known about the cognitive behavior, norms, and attitudes of the drivers under emergency evacuation.

In general, evacuation from disasters with long enough lead warning time (from hours to days) such as a hurricane, wildfire, or a far-field tsunami is usually more efficient in comparison to disasters with much less lead warning

The research on evacuation behavior in advance-notice emergency events is vast [14, 15]. However, due to a lack of relevant data, no-notice emergency events have yet to be thoroughly explored. Liu et al. [16] built a logistic regression model to analyze households' child pick-up behavior during such situations, as one of the few research concentrating on evacuation behavior of people during no-notice emergency events.Later, Liu et al. [17] created household gathering and mode choice models and integrated them into a simulation framework to evaluate network performance in the event of a no-notice disaster. Moreover, Golshani et al. [18] used an internet-based stated preference (SP) survey in the Chicago metropolitan region to study people's evacuation participation choice behavior in the event of no-notice disasters. Clearly, there is a significant gap in the literature addressing behavioral analysis of individuals' evacuation decision making in the context of no-notice emergency events.

1.2 Study Objective

This study aims to provide a comprehensive understanding of the decision-making process of residents in case a human-made disaster occurs with an application to Beirut, Lebanon. Specifically, this study examines the following research questions in three different situational contexts (being at home with all family members, having absent family members, and being at work or university when the event occurs):

1. What situational and social factors, information sources, as well as demographic characteristics, influence risk perception?
2. What demographic characteristics influence knowledge perception?
3. What cognitive factors influence the evacuation behavior in a short-lead type of disaster?
4. What receiver characteristics influence the evacuation behavior in a short-lead type of disaster?

1.3 Case Study: Beirut City, Lebanon

A case study area is chosen for the development of the latter framework. In particular, the study area in this thesis is the Municipal Beirut Area and its surroundings, located in the capital of a developing country, Lebanon.

The topographical and geopolitical setting of Lebanon on the eastern Mediterranean increases its vulnerability to both natural and human-made disasters. The recent devastating explosion of Beirut Port on August 4, 2020 resulted in 220 deaths, 6,500 injuries, US$4.6 billion in property damage (See Figure 1.1), and left approximately 300,000 people homeless [19]. This nuclear-scale explosion was a reminder of the vulnerability of the Lebanese population to small- and large-scale disasters. Also, it was an indicator that designing disaster risk reduction strategies is not enough and policies must be implemented.

Although Lebanon has a Disaster Risk Management (DRM) unit, which was established in 2010 in a partnership between the Lebanese government and UNDP

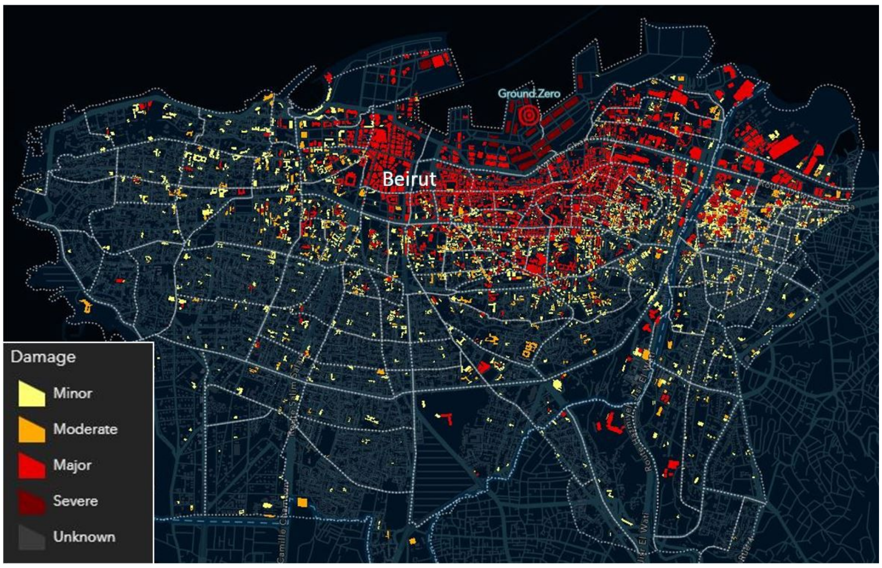

Figure 1.1: A map showing the damaged area due to Beirut Port explosion.

through a project to strengthen the Lebanese government's disaster risk reduction capabilities, this unit didn't respond to the disaster of the Beirut Port Explosion because it is mainly disrupted by political tensions. Accordingly, the disaster of Beirut Port Explosion was not managed in accordance with the requirements of the "Sendai" disaster risk management agreement signed by Lebanon in 2015 and there was lack of coordination among all agencies operating in the field.

The DRM unit is the only national body concerned with all stages of disaster risk reduction, prevention, readiness, response, and disaster recovery.

During normal days, the DRM unit prepares national disaster risk reduction strategies in line with the Sendai 2015–2030 general framework. It also works on operational action plans and updates and develops disaster contingency plans and national response plans. Besides, the DRM unit prepares national standards to measure progress in disaster risk reduction in Lebanon based on Lebanon's commitments to international treaties and to develop and improve early warning systems at the national and local levels. It also collects information to build a national disaster risk management database, and it coordinates studies to identify risk types and develop precautionary plans to reduce them. In addition, it works on raising awareness and developing skills at the local level through awareness campaigns and workshops in schools and municipalities in various Lebanese provinces.

Moreover, during disasters and crises, the DRM unit role is the following:

- Receive calls about the occurrence of a disaster or a crisis and report it besides generalizing it to all relevant departments and bodies to take immediate measures to address the disaster or crisis and take necessary measures to cope with disasters and crises.

- Propose appropriate decisions to manage and address the disaster or crisis in coordination with relevant departments and bodies.

- Activate communication and coordination with and between all intervention agencies during operations.

- Prepare and circulate the Humanitarian Appeal for various stages of disaster management with states and international bodies.

- Follow-up responses at the national level.

- Assess the results of the post-operation intervention and propose measures to help improve future performance.

- Follow-up recovery work at the national level.

1.4 Research Significance

Generally, this study would provide a comprehensive understanding of the rationale behind evacuation decision-making in the context of sudden-human made disasters, subsequently extending the literature on behavioral analysis of individuals' evacuation decision making in the context of no-notice emergency events. Furthermore, through the case study of Beirut city, Lebanon, this study would capture the factors that influence the behavioral response to a human-made hazard in a developing country as compared to most of the literature, which typically investigates such factors in regions such as the U.S.A. and Asia-Pacific.

Specific to the case study, being Beirut city, the proposed research allows the identification of proper interventions that assist in responding to human-made disasters. Moreover, understanding the evacuation decision-making process will assist the DRM unit of Lebanon in developing emergency evacuation strategies that: understand the public's evacuation behavior; customize city-specific evacuation logistics; optimize the dissemination of evacuation information.

Finally, the framework can be applied in different cities in Arab countries. The Arab world is prone to violence and terrorism as well as severe natural hazards and human-caused threats like fires, oil spills, and red algae [20]. Cities in the Arab world are vulnerable because they are unprepared for disasters and may suffer economic and financial losses as a result of limited coping (i.e., the ability to mitigate negative consequences once a disaster occurs) and adaptive (long-term plans to transform the settlement into a resilient city) capacities [20]. Jeschonnek et al. [21] research revealed that most Arab countries, rich or poor, lack both coping and adaptive capabilities. Thus, the application of the developed framework in different cities in Arab countries is essential.

1.5 Thesis Structure

The rest of this thesis is structured as follows. The second chapter presents a literature review on the evacuation modeling methods and the Protective Action Decision Model (PADM) stages. The third chapter specifies the study objectives, modeling approach, and study approach. The fourth chapter explains the concept of structural equation modeling. The fifth chapter describes the study area, explains the procedure used to collect data, and presents the descriptive findings. The results of the exploratory factor analysis and structural equation modeling are presented and discussed in chapter six. Finally, chapter seven presents the study's most important conclusions, research implications and suggests extensions of this work.

Chapter 2

Literature Review

This chapter consists of five sections. Section 2.1 focuses on the theoretical frameworks that have been used to address disaster preparedness. Section 2.2 explains the stages of the Protective Action Decision Model (PADM). Sections 2.3 and 2.4 provide an overview of the evacuation modeling methods. Finally, the gaps in the literature are stated in Section 2.5, along with the drivers behind this research topic.

2.1 Theoretical Frameworks

Protective/precautionary action theoretical frameworks, such as the Protective Motivation Theory (PMT) and Protective Action Decision Model (PADM), have traditionally been used to address catastrophe preparedness [22].

Initially, the PMT was developed by Rogers in 1975 [23] to describe how people are motivated to react in a self-protective manner in the face of a perceived health hazard. PMT is now commonly used to explain self-protective behaviors in disaster situations [24, 25, 26]. PMT focuses on individuals' cognitive processes prior to taking protective actions, which include two appraisal processes:

threat appraisal (i.e., perceived probability and severity of disasters) and coping appraisal, which includes response efficacy (i.e., perception of preparedness effectiveness), self-efficacy (i.e., perceived ability to carry out protective actions), and response cost (i.e., perceived costs related to taking protective actions) [27, 24].

On the other hand, the PADM was developed by Lindell and Perry 1992 [28] to provide a holistic approach to human behavior in emergency situations. PADM emphasizes several perceptions that are important for decision-making to take protective action, including threat perceptions (i.e., individuals' expectations of personal impacts from disasters, such as perceived disaster consequences), protective action perceptions (i.e., hazard-related and resource-related attributes of hazard adjustments, such as effectiveness and cost), and stakeholder perceptions (i.e., stakeholders' power over each other) [1]. The PADM can be used to examine these perceptions in response to a disaster or environmental hazard or in relation to how they influence decision-making before the occurrence of threats [1].

PADM and PMT share some similarities but also have significant differences [23, 27, 29]. A common factor that the two frameworks account for is subjective perception and the cognitive processes that lead to action and deviation from normalcy. Moreover, PADM's definition of hazard-related attributes (person and property protection, as well as utility for other purposes) is similar to, but more expansive than, PMT's response efficacy [1]. On the other hand, PADM's definition of resource-related attributes (cost, time and effort requirements, knowledge and skill, and required cooperation) differs significantly from PMT's because the latter appears to be most closely related to the knowledge and skill component of the resource-related attributes [1]. Furthermore, the resource-related attributes are characteristics of a protective action, whereas self-efficacy is a personal characteristic [1].

2.2 Protective Action Decision Model (PADM) in Evacuation Modeling

The PADM (See Figure 2.1) establishes a descriptive framework of the information flow and decision-making that influence protective actions taken in response to disasters [30, 31, 32, 33]. The model describes the path from the primary perception of hazard cues to the start of protective action. In addition, it emphasizes the importance of appraisal processes, and thus connects cognitive psychological approaches such as the transactional stress model, with conventional safety engineering models. According to the PADM, the environmental cues, social cues, warnings, and other human characteristics can influence the evacuation decision [1].

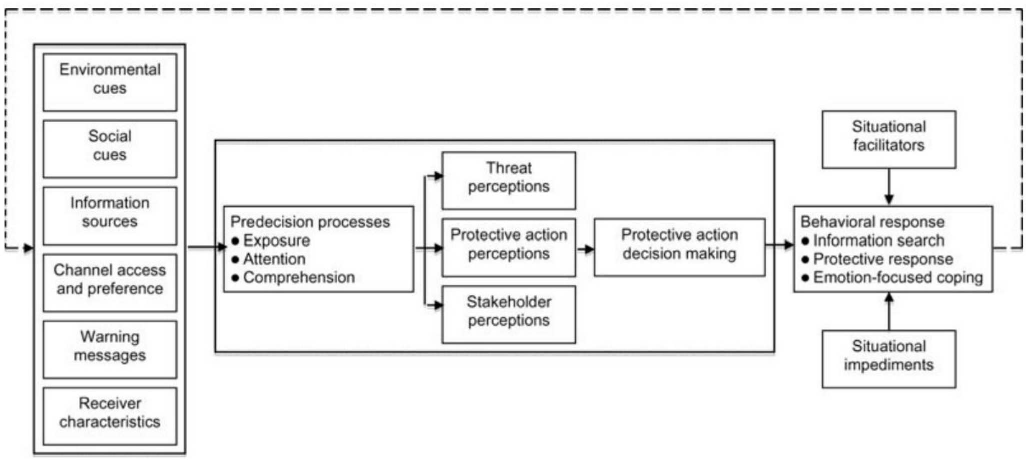

Figure 2.1: Protective Action Decision Model [1]

The subsections that follow go over the stages of PADM.

2.2.1 *Social and Environmental Cues*

According to the PADM, a person receives a variety of cues about the impending risk and danger of an extreme event, including environmental and social cues.

Environmental cues are sights, smells, or sounds that indicate the onset of a threat. For example, the sight of a funnel cloud and a freight train-like sound are clear indicators of impending danger in tornadoes.

Social cues are formed as a result of observations of other people's behavior. According to the PADM, social cues can influence the evacuation decision [1]. The social influence results in a follow-the-crowd phenomenon [34]. This could be due to the feeling of safety in numbers that following others can bring [35]. Moreover, families, relatives, friends, neighbors, and coworkers impact evacuation decision-making [36]. Family relationships typically have a greater influence on evacuation decisions than community relationships [37].

2.2.2 *Sources of Information*

The dissemination of the social information is based upon the traditional six-component communication model of source-channel-message-receiver-effect-feedback [38, 39, 40]. Sources in the social context consist of other people who may communicate information about risks and protective measures, as well as provide support to decrease the hazard or provide material resources that aid protective response. Authorities, the news media, and peers (friends, relatives, neighbors, and coworkers, for example) can all provide information about the hazard and alternative protective measures.

2.2.3 *Warning Messages and Channel Access and Preference*

Warnings are messages that are sent from a source to a receiver via a channel, resulting in effects that vary depending on the receiver's characteristics [1]. The warning network, which consists of a network of organizations and individuals, is an important part of the social context [41, 42]. The warning network can send information through a variety of channels. These channels include sirens, the media, emergency broadcast stations, human contact, and specific systems like automatic telephone ring-downs and tone-alert radios [43]. These channels differ in terms of dissemination rate and precision, penetration of normal activities, message specificity/distortion, sender and receiver equipment requirements, and feedback/receipt verification. Besides the official warning system, peers transmit information through informal warning systems. Even if peers do not overtly send out warning signals, their actions—particularly visible evacuation preparations—can serve as social cues for taking precautionary action [44]. In addition to formal messaging, individuals frequently use social networks to gather information to support decision-making [45].

2.2.4 *Receiver Characteristics*

Characteristics of the receivers include their physical (e.g., strength), psychomotor (e.g., vision and hearing), and cognitive (e.g., primary and secondary languages as well as their mental models/schemas) abilities as well as their economic (wealth and vehicles) and social (friends, relatives, neighbors, and co-workers) resources [1]. According to the PADM, receiver characteristics, such as demographics, can influence the decision-making process. For example, the evacuation decision is typically found to be positively correlated with female gender, children at home, and education level, while negatively correlated with age, household size, and homeownership [46]. The inability to evacuate is frequently associated with race, income, disability, and health status [47]. The ability of older populations to evacuate is more limited and they are more likely to remain behind to protect their property [48, 49, 50, 51]. Moreover, length of residence, homeownership, age, income, and employment status influence the decision of whether to evacuate [52].

2.2.5 *Psychological Processes*

According to the PADM, in the second stage of decision-making, a person engages in pre-decision processes that determine his or her perceptions of risks (or threats), perceptions of possible protective actions in a given situation, and perceptions of stakeholder actions (i.e., the responsibilities of various actors in a given situation). The predecisional processes are exposure (being in a position to acquire threat information from the environment or other people), attention (noticing the information that is available), and interpretation of environmental cues or comprehension of warning messages [53]. Threat perception refers to the public's awareness of potential risk; protective action perception refers to the public's awareness of one's own ability to take protective action; and stakeholder perception refers to the public's awareness of governments' and other agencies' ability to respond to disasters [54]. Protective action perception can be divided into two types: hazard-related perception and resource-related perception [1, 55], which refers to public awareness of protective action effectiveness and resource input value in protective action, respectively.

2.2.6 *Cognitive Factors*

2.2.6.1. *Risk Perception*

Risk perception plays an essential role in the PADM. It is understood as a threshold mechanism for evacuation decision-making as theorized by the PADM [56]. According to previous studies [57, 58], risk perception is the subjective assessment of the probability of an undesirable event, the magnitude of its consequences, and one's skills for coping. Risk perception has been measured in several ways. The most common have been one or more questions about the likelihood or probability that an event would occur in the future. Many measures include questions about whether a future event would cause harm to oneself, family, household, friends, neighbors, or peers [59, 60, 61, 62]. Measures have included the likelihood of damage occurring to the respondent's property, the areas in which she or he lives, the community, or the region [63, 64, 60, 62].

A meta-analysis from selected literature on risk perception from various disciplines focusing on natural hazards was conducted by Wachinger et al. [58]. The key factors for determining risk perceptions were found to be four categories: Risk factors – which are the perceived likelihood and the perceived or experienced frequency of an event, Informational factors – which are the source and level of information, media coverage, involvement of experts in risk malmanagement, Personal factors which include age, gender, profession, personal disaster experience, etc., and Contextual factors – which include family status, area of residence, vulnerability indices, etc.

For example, the information provided by the mass media affects risk perception, only if the respondents lack direct experience [65]. Also, it was found that trust in authorities and confidence in protective measures influence risk perceptions [66, 67, 68]. Some studies have found that age and gender have an influence on risk perception [69, 70, 71, 72], while others found no or little influence [73, 65, 74, 75]. For example, the World Trade Center (WTC) evacuation study conducted by Sherman et al. found that being female was associated with increased perceived risk [76] and studies of hurricane evacuation showed that women are more likely to evacuate than men [77, 78]. Moreover, some authors argue that older adults are better at risk assessment than younger adults because they have to make risk-related decisions more frequently in their daily lives (e.g., medication labeling adaptation to changes in physical fitness) [79, 80]. When comparing homeowners to non-homeowners, Wei et al. [81] found that homeowners were more likely to have greater risk perception.

Risk perception was found to be positively correlated with the adoption of protective responses in studies focused on threats of terrorist attacks [82, 83]. For instance, several studies on the attacks on the World Trade Center (WTC) on September 11, 2001, found that high perceived risk was correlated with the probability to make evacuation decisions and faster response times, and low perceived risk was related to delayed evacuation [84, 85, 32, 76]. Further, Gershon et al. [86] reported that 70% of the interviewed WTC occupants stated that their evacuation decision was triggered by feeling at risk.

2.2.6.2. *Knowledge Perception*

Although not stated in the PADM, knowledge perception impacts behavioral intentions. Knowledge influences behavior by acting as a guideline for action [87]. Buylova et al. [88] found that knowledge perception is a significant predictor of evacuation intentions.

2.2.7 *Situational Impediments and Facilitators*

According to the PADM, threat perception, protective action perceptions, and stakeholder perceptions serve as the foundation for protective action decision-making, which results in a behavioral response when combined with situational facilitators and impediments [1]. The actual execution of behavioral responses is influenced not just by people's intentions to do such actions, but also by conditions in their physical and social environments that might obstruct or promote activities that they did not want to take [89]. Most of the time, the lack of correspondence between protective action intentions and behavior is caused by impediments rather than unexpected facilitators. For example, there have been numerous cases where people wanted to evacuate but lacked access to a personal vehicle [4, 90], lacked personal mobility due to physical handicaps [91, 92], or lacked a safe location to visit and a safe route to take [93]. Another impediment includes the separation of family members. According to Drabek and Boggs [94], evacuation is unlikely to occur until family members have been reunited or separated family members can establish communication contact and agree on a meeting location. Moreover, previous research on evacuation decision-making has revealed that household demographic characteristics can either be situational impediments to or facilitators of household evacuation. According to Dash and Gladwin [3], households with higher incomes are more likely to evacuate from imminent storm risks than households with lower incomes because of the greater availability of resources that aid evacuation. Also, they discovered that households with young children (under the age of 10) were more likely to evacuate than households without children; conversely, families with members over the age of 45 were less likely to flee.

2.3 Evacuation Modeling Using Statistical Methods

Several studies have been conducted to analyze risk perception and evacuation decisions in natural hazard scenarios. Multiple linear regression analysis was used to assess the factors that impact the flood risk perception [95, 96] and disaster preparedness [97]. Kellens et al. [95] used a multiple linear regression analysis to understand the various personal, experiential, and residence characteristics contributing to the flood risk perception along the Belgian coast. On the other hand, Miceli et al. [97] studied perception and disaster preparedness for flood risk in a group of people living in an alpine valley in the north of Italy. Multiple linear regression analysis was conducted to analyze the relationship between adoption of protective behaviors and perception of flood risk while controlling the effects of socio-demographic and experiential characteristics on the adoption of protective behaviors. Chen et al. [98] studied the public risk perceptions and behavioral intentions in the event of a Cascadia Subduction Zone (CSZ) earthquake and local tsunami on the Oregon Coast. The primary objective of the study was to determine the main predictors of evacuation intended behaviors among socio-environmental and cognitive factors. An Ordinary Least Squares (OLS) regression analysis was used to determine the predictors of two dependent variables which are evacuation behavioral intentions and pre-evacuation behavioral intentions.

Moreover, Chen et al. [99] used the Protective Action Decision Model (PADM) as a guide to analyze coastal residents' risk perceptions, perceptions of hazard knowledge and evacuation mode efficacy, evacuation intentions, and evacuation mode choice during tsunami for two coastal communities in the Cascadia Subduction Zone. To examine the relationships between these variables and explore the multi-stage process of decision making, Chen et al. [99] used Pearson correlation, ordinary least squares (OLS) regression, and binary logistic regression analyses. Ao et al. [100] used a binary logistic regression to study the impact of Built Environment (BE) and risk perception on the seismic evacuation behavior of residents from the areas affected by the Wenchuan earthquake after a decade. A stepwise method was used to explore the contribution of each type of variable to the proposed model when running the binary logistic regression. Burnside et al. [101] used a logit model to explain factors affecting the hypothetical evacuation behavior of residents from the Greater New Orleans area if they were faced with the possible landfall of a major hurricane.

2.4 Evacuation Modeling Using Microsimulation Approach

Since collecting real-time driving behavior data under emergent scenarios is challenging, several studies resorted to using microsimulation studies to evaluate the impact of driving behavior on evacuation efficiency [102]. Tu et al. [103] simulated the effect of driving behavior on evacuation clearance time. The results of this study showed that increases in acceleration rate and in maximum speed do not have a significant impact on the evacuation clearance time. Also, this study found that a reduction both in mean headway and in minimum gap significantly reduces the evacuation time.

Further, Kostovasili and Antoniou [102] investigated drivers' aggressiveness impact on the evacuation efficiency. The results of their study showed that reducing the evacuation time can only be achieved by reversing the most congested links when the driver follows a more defensive approach. On the other hand, if the drivers are more aggressive, the reversal of the links does not reduce the minimum required evacuation time because the capacity and the size of the network require a specific evacuation time regardless of the driving behavior. Besides, Yuan et al. [104] developed and implemented an agent-based simulation system that uses a multi-layer hierarchical decision-making process to mimic each agent's driving behaviors. The results demonstrated that it is beneficial to incorporate more variability in driving behaviors into a model because they are expected in an evacuation situation.

2.5 Research Gap

Extensive research has been conducted on the factors that affect emergency evacuation efficiency. However, less is known about the risk perception and variation in behavior in short-lead disaster evacuation [105, 106, 107]. Besides, several studies on natural and environmental hazards have applied the Protective Action Decision Model (PADM), including earthquakes [108, 109], tsunamis [81, 48], hurricanes and tornadoes [110, 111], and volcanic eruptions [112, 113]. To the best of the author's knowledge, no research has used the PADM for a human-made disaster. Using structural equation modeling (SEM), this study uses the PADM framework to explain intention toward evacuation behavior before a human-made disaster. The SEM was adopted because of its ability to handle complex relationships in which some variables can be subjective or unobserved. Another reason is that SEM is a preferred alternative to regression analyses for testing mediation.

Chapter 3

Study Objectives and Approach

This chapter presents the theoretical framework, modeling approach, and study approach.

3.1 Theoretical Framework

Based on the literature review and the PADM, this study designed and developed an SEM-based model to examine the factors that influence the behavioral response to a human-made hazard.

First of all, it is vital to explain that some PADM variables were operationalized to aid research on behavior and decision-making in rapid-onset human-made disasters.

According to the PADM, the environmental cues, social cues, warnings, and other human characteristics can influence the evacuation decision [1]. Moreover, risk perception plays an essential role in the PADM. It is understood as a threshold mechanism for evacuation decision-making as theorized by the PADM [56]. In this study, the risk perception measures include questions about the likelihood of a terrorist attack or act of war occurring in Beirut in the next 12 months, the likelihood this event to lead to injuries to self or family, create a life-threatening situation to self or family, severely damage or destroy respondent's home, and destroy or severely damage roads.

In the case of a human-made hazard (terrorist attack or act of war), there would be no environmental cues, so we had to modify this component of the PADM framework for the context of our study. The signs of destruction to the surrounding environment were considered to be the main sign of terrorism. Hence, we hypothesized that:

- H1- Signs of destruction to the surrounding environment influence risk perception.
- H2- Social cues represented by the behavior (evacuating/not evacuating) of loved ones and neighbors influence risk perception.
- H3- Individuals' socio-demographic characteristics influence knowledge perception.
- H4- The strong governmental disaster response and the recommended course of action by the government are warnings that influence risk perception.
- H5- The sources of information and their preferences influence risk perception.

In this study, knowledge perception measures include questions about confidence in knowing the government's emergency evacuation strategy, what safety measures to take, evacuation routes from home to potential evacuation destinations, and having an emergency plan. We hypothesized the following:

- H6- Individuals' socio-demographic characteristics influence knowledge perception.

According to the PADM framework, cognitive factors influence behavioral response. Hence, we hypothesized that:

- H7- Risk perception influences evacuation behavior.

- H8- Knowledge perception influences evacuation behavior.

In this study, we do not examine stakeholder views as indicated in PADM. We assume that, on average, a person would view an evacuation in the event of a human-caused hazard (terrorist attack or act of war) as a personal responsibility due to the lack of time for authorities to directly assist in the event of a sudden-onset disaster.

Situational impediments and facilitators were indirectly presented in our model by asking the respondents about their potential behavioral response to the event in the following situations: being at home with all family members, having some of their family members missing, and being at work or school. On the other hand, some facilitators were directly presented in the model. We hypothesized the following:

- H9- Ownership of residence or knowledge of friends/family who owns a residence in a town/village outside of Beirut in Lebanon is an evacuation facilitator that influences evacuation behavior.

- H10- Knowledge of evacuation destinations (inside or outside Lebanon) influences evacuation behavior.

All the above hypotheses are represented in a path model (See Figure 3.1).

Finally, in this study, we examine if the effect of the receiver characteristics on the evacuation behavior can take an indirect path through cognitive factors (risk perception and knowledge perception). We examine the following hypotheses:

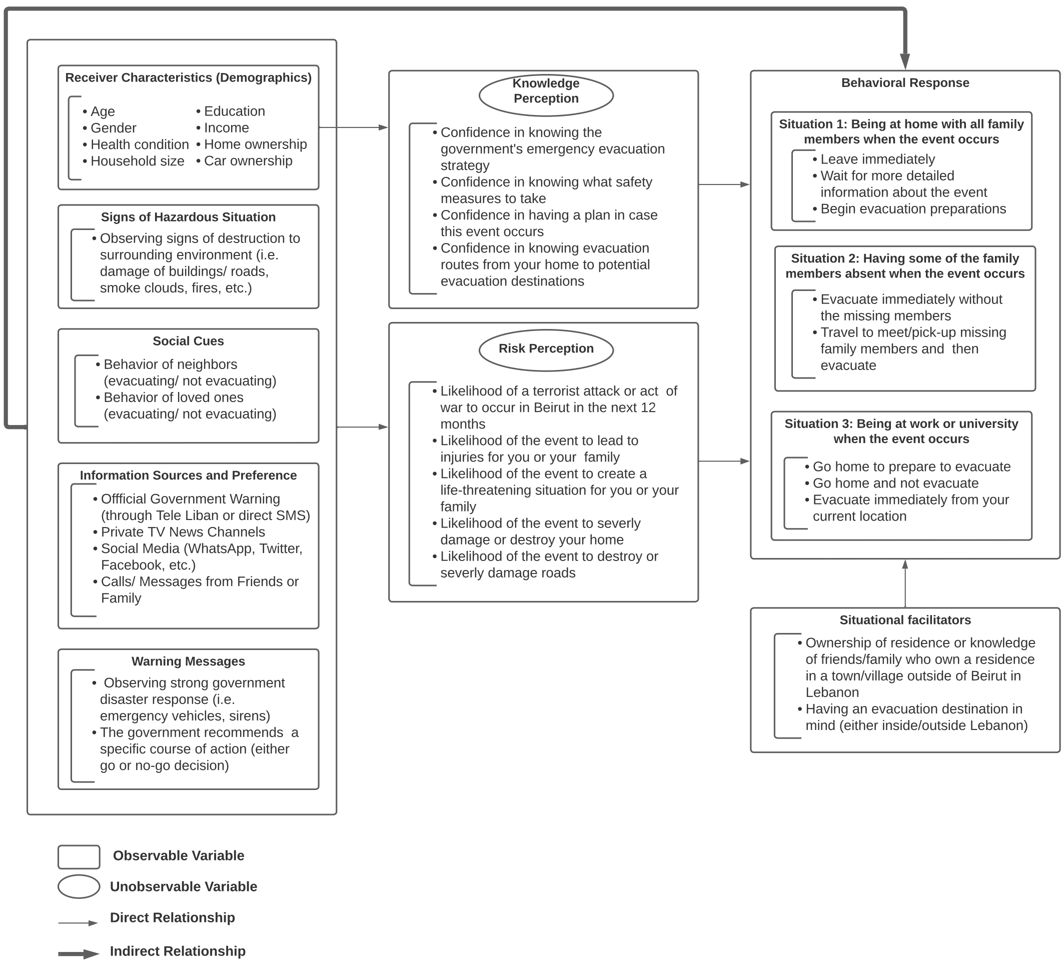

Figure 3.1: The theoretical framework used to study decision-making in rapid onset human-made disaster.

- H11- Can risk perception mediate the effect of receiver characteristics on evacuation behavior?
- H12- Can knowledge perception mediate the effect of receiver characteristics on evacuation behavior?

3.2 Modeling Approach

This research utilizes Structural Equation Modeling (SEM) to identify and quantify the observed and latent variables that affect the evacuation decision in a short-lead human-made hazard evacuation. SEM is widely used in social and behavioral sciences [114] because of its ability to represent hidden psychological constructs through latent variables and handle measurement errors [115]. The SEM is a multivariate data analysis method that is often used in predicting complex causal relationships between variables [116, 117, 118].

The main advantages of SEM over regression analysis are its ability to **i)** handle complex relationships among variables where some variables can be subjective or unobserved (latent variables); **ii)** account for multicollinearity; **iii)** estimate all the model's coefficients simultaneously and therefore, the significance and strength of a particular relationship in the context of the complete model can be measured; **iv)** obtain more valid coefficients when using latent variables in SEM because it accounts for the measurement error [119, 120, 121, 122].

3.3 Study Approach

After developing the study objectives, a plan was set to achieve them. Figure 3.2 shows the study plan. The first step after designing a web-based survey and collecting the data is to conduct an exploratory factor analysis to identify the number

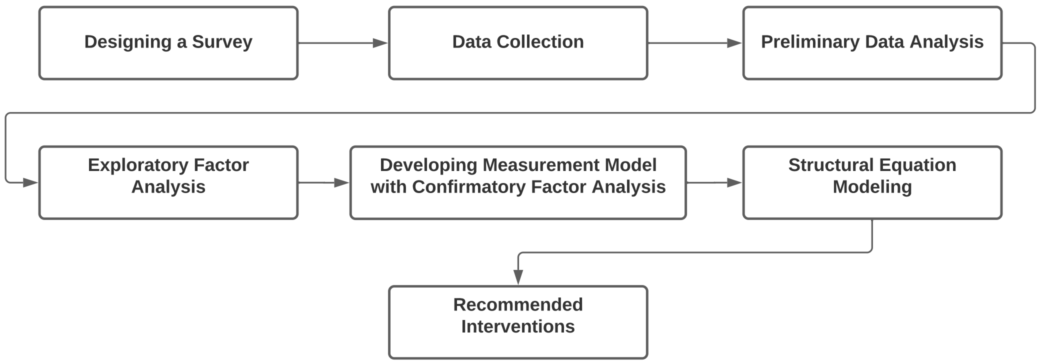

Figure 3.2: Study Plan

of latent variables. Then, SEM is performed to identify the factors that influence evacuation behavior in case of a human-made hazard. A two-step approach for SEM is used, as recommended by [123]. This approach requires developing the measurement model and then simultaneously developing the measurement model with the structural model. To develop an acceptable measurement model, a Confirmatory Factor Analysis (CFA) is performed. The measurement model shows the relations between latent variables and their indicators. Moreover, the structural model captures the causal dependencies between endogenous and exogenous variables [124]. Finally, study results will help emergency planners and policymakers develop emergency evacuation strategies and improve survivability. These steps are described in depth throughout the study.

Chapter 4

Structural Equation Modeling

This chapter consists of five sections. Section 4.1 provides a brief overview of structural equation models with ordinal dependent variables. Section 4.2 explains the detailed formulation of structural equation models. Section 4.3 discusses the estimation method for ordinal observed variables. Section 4.4 discusses model fit indices, and finally, Section 4.5 explains mediation analysis.

4.1 Overview of Structural Equation Models with Ordinal Dependent Variables

The general structural equation model as outlined citebollen1989structural consists of two parts: (1) the structural part that identifies the causal relationships between endogenous and exogenous variables [125], and (2) the measurement part which shows how the latent (or unobserved) variables and their indicators are related [126].

Response variables in behavioral sciences are frequently non-continuous. Ordinal responses have been accommodated by generalizing the conventional structural equation models [127]. The structural equation model with ordinal dependent variables consists of three parts: i) the latent variable model, ii) the first part of measurement equations, which shows the relationships between latent variables and their indicators, and iii) the second part of measurement equations, which is the threshold model for ordinal data.

4.2 Model Formulation

A representation of the modeling framework of the structural equation model with ordinal dependent variables is shown in Figure 4.1. Latent variables which are known as constructs or factors are underlying variables that are not directly observed but are rather deducted from observed variables. On the other hand, observed variables are measured directly from the survey responses. In Figure 4.1, observed variables are shown in rectangles while latent variables are shown in ellipses. Disturbances and error terms are not shown in Figure 4.1.

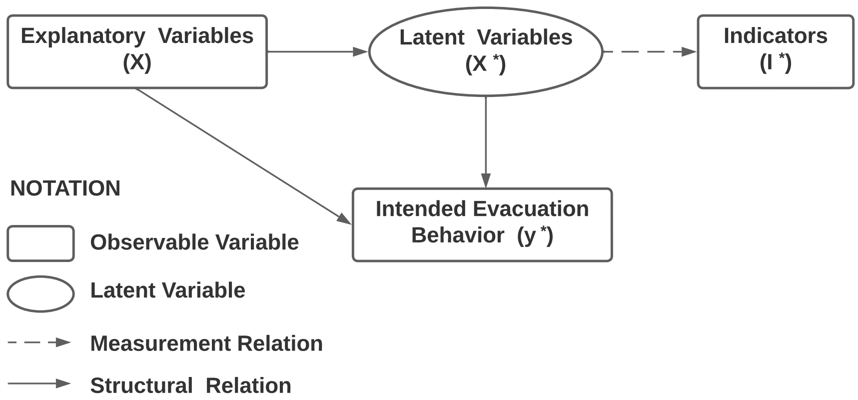

Figure 4.1: Structural Equation Modeling Framework

The model consists of structural equations for the latent variables X^* as well as measurement equations. The latent variables influence the intended evacuation behavior variables and are function of explanatory variables.

4.2.1 ***Intended Evacuation Behavior Variables***

The intended evacuation behavior is an ordinal dependent variable. Therefore, its underlying latent response variable is expressed as a function of latent variables and explanatory variables as follows:

$$y^*_{l,j} = y^*(X, X^*_l; \gamma_{l,j}, \alpha_{l,j}, \epsilon_{l,j}) \tag{4.1}$$

where $y_{l,j}$ is the j^{th} observed intended evacuation behavior, and $j = 1, ..., J$; J is the number of intended evacuation behavior decisions; $y^*_{l,j}$ is the underlying latent response variable of ordinal observed intended evacuation behavior $y_{l,j}$; X is a vector of explanatory variables; X^*_l is the l^{th} continuous latent variable, and $l = 1, ..., L$, where L is the number of latent variables; $\gamma_{l,j}$ is a vector of parameters that multiplies X; $\alpha_{l,j}$ is an unknown parameter; $\epsilon_{l,j}$ is a measurement error term that is distributed as $N(0, 1)$; $y^*(.)$ is a function

We adopt a linear additive representation of equation 4.1 as follows:

$$y^*_{l,j} = \gamma_{l,j} \cdot X + \alpha_{l,j} \cdot X^*_l + \epsilon_{l,j} \tag{4.2}$$

For ordinal observed variables, a threshold model is established as shown below.

$$y_{l,j} = \begin{cases} \mathrm{w}_1 \text{ if } y^*_{l,j} \le \tau_{y_{l,j},1} \\ \mathrm{w}_2 \text{ if } \tau_{y_{l,j},1} < y^*_{l,j} \le \tau_{y_{l,j},2} \\ \vdots \\ \mathrm{w}_V \text{ if } \tau_{y_{l,j},V-1} < y^*_{l,j} \end{cases}$$

where w is vector of ordinal categories for intended evacuation behavior variable $y_{l,j}$; V is the number of categories for $y_{l,j}$; $\tau_{y_{l,j},1}$, ..., $\tau_{y_{l,j},V-1}$ are the threshold parameters relating $y_{l,j}$ to $y^*_{l,j}$.

4.2.2 *Latent Variables Structural Equation*

The latent variables X^* as shown in Figure 4.1 are endogenous. So, any changes in the explanatory variables may influence their values. Latent variable X^*_l is expressed as a function of explanatory variables as follows:

$$X^*_l = X^*(X; \beta, \omega_l) \tag{4.3}$$

where β is vector of unknown parameters; ω_l is disturbance that is distributed as $N(0, \sigma^2_{\omega_l})$; $\sigma^2_{\omega_l}$ is the variance of the disturbance ω_l; $X^*(.)$ is typically a linear function of the unknown parameter vector β as shown below:

$$X^*_l = \beta_l \cdot X + \omega_l \tag{4.4}$$

Correlations between the latent variables are included in the model. Model identification is ensured when every latent variable within the model has an assigned scale, and the model degrees of freedom is greater than or equal to zero [128]. Accordingly, the variances of the latent variables are normalized to one to ensure identification.

4.2.3 *Measurement Equation of the Latent Variables*

The indicators of every latent variable are expressed as a function of the latent variable as follows:

$$I^*_{l,r} = I^*(X^*_l; \lambda_{l,r}, \delta_{l,r}) \tag{4.5}$$

where $I_{l,r}$ is the r^{th} indicator of latent variable X^*_l and R^l is the total of the number of indicators of X^*_l; $I^*_{l,r}$ is the latent response variable underlying the ordinal observed indicator $I_{l,r}$; $\lambda_{l,r}$ is an unknown parameter; $\delta_{l,r}$ is a measurement error term that is distributed as $N(0,1)$; $I^*(.)$ is a function.

Typically, the vector of latent response variables is expressed as follows:

$$I^*_{l,r} = \lambda_{l,r} \cdot X^*_l + \delta_{l,r} \tag{4.6}$$

For ordinal observed variables, a threshold model is established as shown below.

$$I_{l,r} = \begin{cases} \mathrm{z}_1 \text{ if } I^*_{l,r} \le \tau_{I_l,r,1} \\ \mathrm{z}_2 \text{ if } \tau_{I_l,r,1} < I^*_{l,r} \le \tau_{I_l,r,2} \\ \vdots \\ \mathrm{z}_Q \text{ if } \tau_{I_l,r,Q-1} < I^*_{l,r} \end{cases}$$

where z is a vector of ordinal categories for indicator $I_{l,r}$; Q is the number of categories for a given variable $I_{l,r}$; $\tau_{I_l,r,1}$, ..., $\tau_{I_l,r,Q-1}$ are the threshold parameters relating $I_{l,r}$ to $I^*_{l,r}$.

4.3 Model Estimation

Model estimation entails calculating a value for each unknown (free) parameter in the specified model. However, it goes far beyond this simple goal, as the estimated values must allow generating a covariance matrix that is as close to the observed covariance matrix as possible. It is an iterative procedure whose general principle is to begin with an initial value (specified for the set or for each individual parameter either by the user or automatically by the software) and gradually refine it through successive iterations that stop when no new value for each parameter reduces the difference between the observed and reproduced covariance matrices.

The most commonly used method for estimation in SEM software is the Maximum Likelihood (ML) method which requires that variables are continuous and multivariate normal. However, there are at least two problems with utilizing this estimator in the humanities and social sciences. First, ordinal (for example, Likert-type scale) and dichotomous/binary (true/false) are both common outcome measures (indicators). Second, there is a high prevalence of data that is not normally distributed. Moreover, in the cases where the data is not normal or has excessive kurtosis, usage of the ML method may lead to incorrect standard errors, t-tests, chi-square, and other significance tests [129].

Accordingly, an alternative estimation method to ML is used, which is the Diagonally Weighted Least Squares (DWLS) method. Jöreskog and Sörbom [130] recommended adopting this method when the sample size is small and the data is non-normal. This estimator, which is based on the polychoric or polyserial correlation matrix, is a compromise between the unweighted least squares method and the full weighted least squares method [130]. Two "robust" versions of DWLS that are similar to this estimator, known as "WLSM" and "WLSMV" in lavaan, provide corrected estimates that improve solution outcomes (standard errors, X^2 , fit indices described as "robust").

4.4 Model Fit

The term "model fit" refers to how well the specified model (estimated covariance matrix) represents the data (observed covariance matrix). The model fit test is used to determine how well the model's overall structure fits the data. A good model fit does not imply that every aspect of the model is well-fitting. A poor fit, on the other hand, means that the data does not match the model.

Regarding the SEM model's fit indices, Kline [131] recommends reporting at least the (1) model chi-square, (2) the Steiger-Lind root mean square error of approximation (RMSEA) with its 90 percent confidence interval, (3) the Bentler comparative index (CFI), and (4) the standardized root mean square residual (SRMR). Below is an explanation of the aforementioned model fit indices.

The chi-squared statistic is used to test the null hypothesis that the model fits the population perfectly [132]. Chi-square is very sensitive to sample size. A "relative chi-square" test, which is the chi-square value divided by the degrees of freedom, is a preferable alternative to chi-square, as it is less dependent on sample size. This ratio should be less than 5 [133]. However, Ullman recommends a lower ratio, being less than 2, as an indicator of a good fit [133].

The Root Mean Square Error of Approximation (RMSEA) is an absolute fit indicator that measures how close a hypothesized model is to being perfect. An RMSEA value of < 0.05 indicates a "close fit," and a value < 0.08 indicates a reasonable model–data fit, according to previous research [134, 135].

The Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), on the other hand, are incremental fit indices that compare a hypothesized model's fit to that of a baseline model (i.e., a model with the worst fit). According to a study conducted by Hu and Bentler [136], the comparative fit index (CFI) and Tucker–Lewis index (TLI) should both be better than 0.95.

The Standardized Root Mean Square Residual (SRMR) is the average difference between the anticipated and observed covariances in the model based on standardized residuals. It is a badness of fit test that is similar to RMSEA, in which the higher the value, the worse the fit. A good fit is defined as an SRMR of 0.05 or less, while an adequate fit is defined as an SRMR of 0.05 to 0.09 [137].

4.5 Mediation

Mediation analysis is used to determine how an antecedent variable (X) influences an outcome variable (Y) through one or more intervening variables, known as mediators (M).

Before explaining types of the mediation, some terminologies such as direct effect, indirect effect, and total effects must be clarified. A direct effect is simply when an independent variable and a dependent variable have a direct relationship. An indirect effect is the association that flows from an independent variable through a mediator and subsequently to a dependent variable. The combined influence of the direct effect between two constructs and the indirect effect passing through the mediator is referred to as the total effect.

There are two types of mediation: full mediation and partial mediation. Full mediation is when the direct effect between two constructs is not significant, but the indirect effect through the mediator does have a significant relationship

[138]. On the other hand, partial mediation is when the direct effect between two constructs and the indirect effect through the mediator are significant [138].

Figure 4.2 shows a conceptual depiction of a parallel mediation model with two mediators. The model shows that X affects Y in three ways: directly through path c and indirectly via M_k through paths a_k and b_k, k$= 1, 2$. These pathways are statistically described by two equations using linear regression.

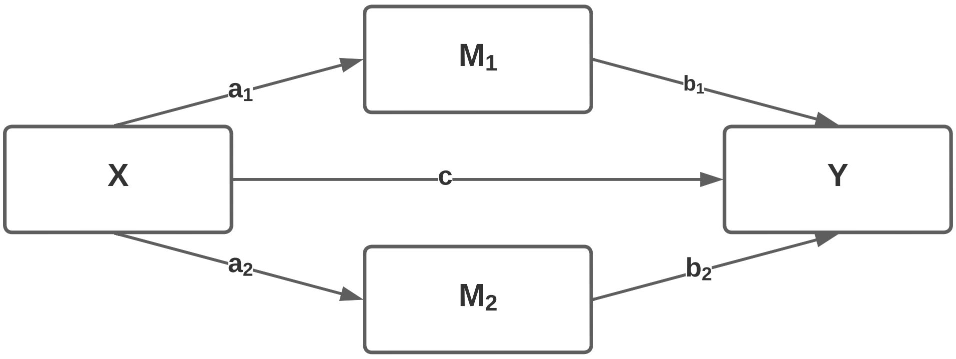

Figure 4.2: Conceptual representation of a parallel mediation model with two mediators.

$$M_k = i_{M_k} + a_k X + \epsilon_{M_k} \text{ for all k} \tag{4.7}$$

and

$$Y = i_Y + cX + \sum_{k=1}^{2} b_k M_k + \delta_Y \tag{4.8}$$

These equations specify how each of the pathways in Figure 4.2 is statistically estimated. Substituting Equation (4.7) into Equation (4.8) and collecting terms provides the following model, which shows how to calculate direct and indirect effects.

$$Y = i_Y^* + (c + a_1 b_1 + a_2 b_2)X + \epsilon_Y^* \tag{4.9}$$

where $i_Y^* = i_Y + \sum b_k^* i_{M_k}$ and $\epsilon_Y^* = \delta_Y + \sum b_k^* \epsilon_{M_k}$.

The total effect c' is the sum of the direct and indirect effects.

$$c' = c + \sum (a_k b_k) \text{ for k = 1 and 2} \tag{4.10}$$

In the absence of any mediators, the total effect c' is the coefficient that would be statistically estimated if Y was regressed onto X alone.

Chapter 5

Study Area and Data Collection

This chapter describes the study area and the data collection. It focuses on the data collection method, survey instrument, and data cleaning. Then, the descriptive statistics of the collected data are presented.

5.1 Study Area

A survey was conducted in the Municipal Beirut Area and its surroundings to study the evacuation behavior intent of its population as a result of a human-made disaster (terrorist attack or act of war). The study area was not limited to the Municipal Beirut Area but extended to Dahieh (Ouzai, Chiah, and Haret Hreik), Bourj Hammoud, Sin El Fil, Bouchrieh, Jdiedeh, and Dekweneh because buildings in these areas were exposed to the Beirut Port explosion, and thus this area is not safe (See Figures 5.1 and 5.2).

The study site focuses on the downtown area of central Beirut (the old city), in which the transportation network has not witnessed a significant enhance-

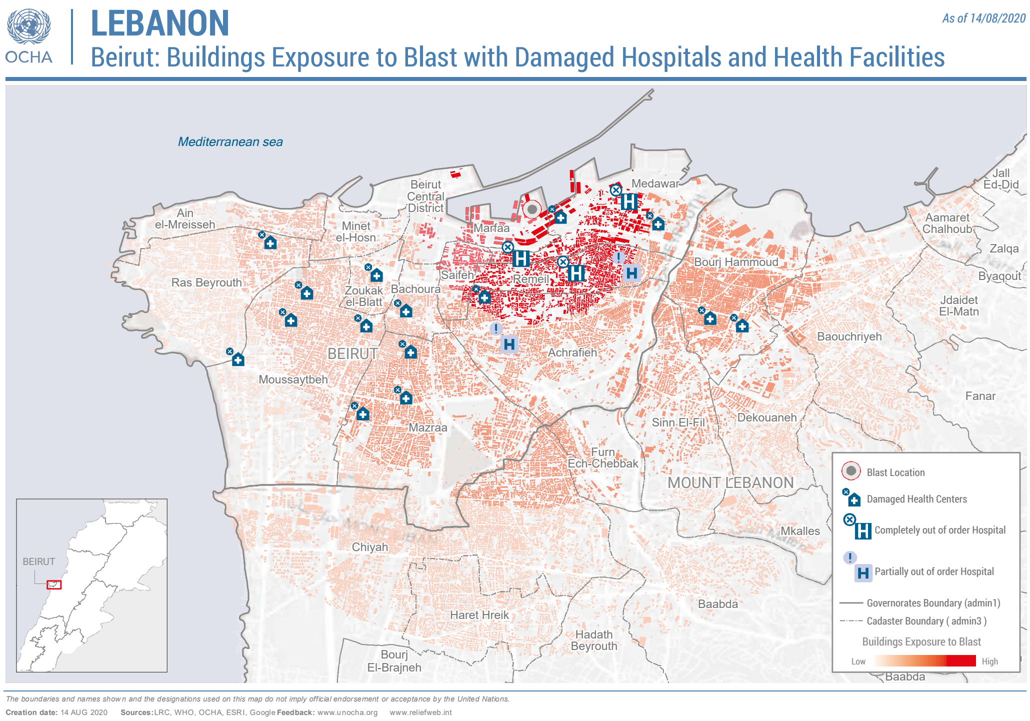

Figure 5.1: Map Showing Beirut Buildings Exposure to Blast with Damaged Hospitals and Health Facilities [2]

Figure 5.2: Map Showing the Study Area

ment over the last decades. Besides, the road network of Beirut consists of 2% motorways, 22% primary roads, and 12% secondary, while the rest are tertiary, residential, or unclassified roads [139]. The aforementioned road classification as well as the topology and node distribution of the transportation network increase its vulnerability and sensitivity to extreme events.

5.2 Data Collection

To answer the research questions related to the evacuation behavior intent in case of a human-made hazard (terrorist attack or act of war), a PADM-based survey was conducted between February 2021 and February 2022 in the Municipal Beirut Area and its surroundings. At the beginning of the data collection, the population of licensed drivers who are aged between 18 and 65 years old and work/study and/or reside in the Municipal Beirut Area and its surroundings was targeted. However, there was a low response rate from respondents that belonged to age categories greater than 30. Thus, the focus was then only on the younger generation of licensed drivers because the group of people reached through online surveys are mainly tech-savvy, young, and highly educated and this leads to the exclusion of other age groups (i.e. elderlies who tend to be less tech savvy) [140].

The web-based survey was designed using the LimeSurvey platform, and it was approved by the Institutional Review Board (IRB) at AUB. The survey link was distributed over local social media pages (Facebook, Instagram, and WhatsApp groups). Also, it was sent by email to one thousand five hundred students at the American University of Beirut, Also, it was sent by email to one thousand five hundred students at the American University of Beirut, chosen at random. Participants were asked to complete the survey online due to the difficulty of personal contact during the COVID-19 pandemic. The incomplete responses have been removed, resulting in a sample size of 266 responses.

5.3 Survey Instrument

In answering the survey questions, respondents were asked to assume that it is 3:00 pm on a weekday. Also, they were asked to consider the case where a human-made hazard (such as a terrorist attack or act of war) may occur in Beirut. The survey consisted of four sections. Below is a description of each section of the survey.

- Section 1. This section focused on understanding the respondents' risk perception, as well as knowledge and preparedness for a short-lead human-made disaster. Besides, they were asked about the source of information they would go for in this event.

- Section 2. This section focused on understanding the respondents' evacuation behavior intentions in the case of a sudden human-made disaster. The participants were asked about the likelihood of adopting certain courses of action in the following scenarios: 1) being at home with all their family members when the event occurs, 2) having absent family members when the event occurs, 3) being at work/university when the event occurs.

- Section 3: In this section, respondents were asked about evacuation logistics, such as evacuation mode choice, evacuation route, and evacuation destination.

- Section 4. In this section, respondents were asked about their socioeconomic characteristics.

5.4 Data Cleaning

Out of the 1500 students, 434 started the survey (28.9% of the student population). Only 213 students (14.2% of the student population and 80.1% of respondents) completed the survey, whereas the remaining 213 only submitted partial responses.

Regarding the data collected from social media pages, 308 individuals started the survey. Only 45.7% of the participants submitted complete responses, whereas 54.3% submitted partial responses. Moreover, only 53 responses out of the complete responses met the survey criteria. So, the remaining complete responses were excluded from the analysis.

The partial responses were excluded from the modeling process because they lacked crucial information for the model.

5.5 Data Description

The collected data is segregated into two groups: those who work or study in Beirut (256 responses out of 266) and those who reside in Beirut (162 responses out of 266).

Table 5.1 displays the socioeconomic characteristics of the survey participants.

Table 5.1: Socioeconomic Characteristics of Survey Respondents

		Participants who work or study in Beirut (n=256)		Participants who reside in Beirut (n=162)	
Variable	Categories	Frequency	Percentage	Frequency	Percentage
Gender	Male	141	55.1	87	53.7
	Female	115	44.9	75	46.3
Residence Status	Citizen	245	95.7	155	95.7
	Resident	7	2.7	5	3.1
	Refugee	4	1.6	2	1.2
Household Size	1-3	62	24.2	44	27.2
	4-5	147	57.4	86	53.1
	>6	47	18.4	32	19.8
Ownership Status of Current Residence	I am a renter/occupier	37	14.5	30	18.5
	I/family are the primary owners	219	85.5	132	81.5
Car Ownership	Yes	253	98.8	159	98.1
	No	3	1.2	3	1.9
Years of Area Residence	Less than two years	16	6.3	11	6.8
	2-5 years	30	11.7	24	14.8
	More than 5 years	210	82	127	78.4
Language	Arabic	254	99.2	160	98.8
	English	249	97.3	157	96.9
	French	142	55.5	77	47.5
	Other	142	55.5	76	46.9
Education	Secondary/high school diploma	8	3.1	6	3.7
	Some college or university	37	14.5	25	15.4
	University undergraduate/ bachelor's degree or equivalent	139	54.3	89	54.9
	Postgraduate master's degree, doctorate	72	28.1	42	25.9
Occupational status	Student	209	81.6	125	77.2
	Employed	47	18.4	32	19.8
	Unemployed	0	0	5	3.1
Household Monthly Income	0-1,999,000 L.L.	19	7.4	14	8.6
	2,000,000 L.L.-3,999,000 L.L.	26	10.2	16	9.9
	4,000,000 L.L.-5,999,000 L.L.	30	11.7	14	8.6
	6,000,000 L.L.-7,999,000 L.L.	12	4.7	3	1.9
	8,000,000 L.L.-9,999,000 L.L.	16	6.3	12	7.4
	10,000,000 L.L.-14,999,000 L.L.	11	4.3	6	3.7
	15,000,000 L.L.-29,999,000 L.L.	20	7.8	11	6.8
	More than 30,000,000 L.L.	12	4.7	7	4.3
	I don't know/ rather not say	110	43	79	48.8
Respondent or family member with a physical, mental, or emotional condition which may make evacuation more difficult	Yes	52	20.3	31	19.1
	No	204	79.7	131	80.9

Table 5.2 displays the questions stated in section one of the survey and their responses. The mean, and standard deviation for the responses in each sample are presented in this table.

By referring to Table 5.2, five questions are used to measure risk perception. The mean for the responses of the questions related to risk perception for the sample of respondents residing in Beirut is higher than those of the sample of respondents working or studying in Beirut. One apparent difference between the means is for the question of the likelihood of the event destroying or severely damaging the respondent's home (the difference between the means equals 0.18). The reason behind difference is that around forty-one percent of the respondents who work or study in Beirut reside outside it.

As for the mean for responses to questions used to measure knowledge perception, it can be noticed that they are generally low. Looking the mean for the question measuring the confidence of the respondents about knowing the government's emergency evacuation strategy, it has the lowest value in the two samples (mean = 1.27 for the sample of respondents who work or study in Beirut and mean = 1.23 for the sample of respondents that reside in Beirut). This indicates that the respondents lack knowledge of the government's emergency evacuation strategy. Moreover, the descriptive statistics of the remaining questions used to measure knowledge perception indicate that the respondents who reside in Beirut are more confident about knowing what to do when the event occurs. This can be justified by their feeling of vulnerability to such an event. Also, the descriptive statistics of the responses to questions related to risk perception prove this.

Regarding the respondents' preference for the source of information to rely on the incident (order from 1 to 4, 1 being most likely), the descriptive statistics results of the two samples show the following: calls from friends and family rank in the first place, social media rank in the second place, private TV news channels rank in the third place, and official government warning rank in the fourth place.

Moreover, descriptive statistics in Table 5.2 show that it is likely for observing signs of destruction in the surrounding environment and the behavioral response (evacuating or not evacuating) of loved ones to affect the evacuation decisions of the respondents in the two samples. On the other hand, the behavioral response of neighbors had the lowest effect on the evacuation decision of the respondents in the two samples. As for the effect of observing the government's recommended course of action on the evacuation decision, it had a lower effect than that of observing a strong governmental disaster response in the two samples.

Table 5.2: Summary Statistics for Questions in Sections 1 and 2

		Participants who work or study in Beirut (n=256)		**Participants who reside in Beirut (n=162)**	
Category		Mean	Std. Dev.	Mean	Std. Dev.
Risk Perception	Likelihood of a terrorist attack or act of war to occur in Beirut in the next 12 months	3.48	1.095	3.47	1.087
	If such an event occurs tomorrow, how likely/unlikely is it to result in the following?				
	Lead to injuries for you or your family	3.57	0.943	3.59	0.943
	Create a life-threatening situation for you or your family	3.67	1.015	3.70	1.022
	Severely damage or destroy your home	3.44	1.193	3.62	1.076
	Destroy or severely damage roads	4.37	0.839	4.38	0.842
Knowledge Perception	**How confident are you about each of the following statements?**				
	I know the government's emergency evacuation strategy	1.27	0.615	1.23	0.585
	I know what safety measures to take	2.46	1.214	2.51	1.262
	I have a plan in the case of this event	2.21	1.163	2.26	1.203
	I know evacuation routes from my home to potential evacuation destinations	2.33	1.318	2.37	1.332
Source of Information	**Which of the following sources would you be most likely to go for information in this situation?**				
	Official Government Warning (through Tele Liban, direct SMC, etc.)	2.81	1.058	2.88	1.083
	Private TV News Channels	2.77	0.978	2.81	0.969
	Social Media (WhatsAPP, Twitter, Facebook, etc.)	2.59	1.047	2.52	1.004
	Calls/Messages from Friends or Family	1.84	1.114	1.78	1.073
Surrounding Situation	**How likely/unlikely are the following situations to affect your decision to evacuate/not evacuate ?**				
	You see your neighbor evacuating/not evacuating	3.60	1.017	3.53	1.058
	You see your loved one evacuating/not evacuating	4.20	0.887	4.17	0.975
	You observe a strong governmental disaster response	3.90	1.089	3.83	1.177
	The government recommends a specific course of action (either go or no-go decision)	3.61	1.129	3.67	1.091
	You observe signs of destruction of your surrounding environment (i.e. damage to buildings/roads, smoke clouds, fires, etc.)	4.43	0.813	4.41	0.809

* All the variables are measured using a 5-point Likert scale (1:very unlikely to 5: very likely),except the source of information, which is measured using a 4-point rating scale (1 being the most likely)

Table 5.3: Summary Statistics for Likert Scale Questions Related to Intended Behavioral Response

Participants who reside in Beirut (n=162)	Mean	Std. Dev.
Suppose you are at home with all members of your family when this event occurs. How likely/unlikely are you to adopt the following courses of action?		
Leave immediately	3.20	1.180
Wait for more information about the event	3.94	0.970
Begin evacuation preparations	4.09	0.894
Suppose some of you family members are missing when this event occurs. How likely/unlikely are you to adopt the following courses of action?		
Evacuate immediately without the missing family members	2	1.148
Travel to meet/pick-up missing family members and then evacuate	4.40	0.830
Participants who work or study in Beirut (n=256)	**Mean**	**Std. Dev.**
Suppose you are at work/school when this event occurs. How likely/unlikely are you to adopt the following courses of action?		
Go home to prepare to evacuate	3.64	1.064
Go home and not evacuate	3.11	1.077
Evacuate immediately from your current location	3.36	1.290

* The variables are measured using a 5-point Likert scale (1:Very unlikely to 5: Very likely)

Table 5.3 displays the questions stated in section two of the survey and their responses. The mean, and standard deviation for the responses are presented in this table.

The average value for the likelihood of adopting the response of immediately evacuating in the situation of being at home with all family members when the event occurs is the lowest (mean= 3.20) among all the suggested behavioral responses in this situation. Also, descriptive statistics reveal that they are more likely to begin evacuation preparations (mean= 4.09) than wait for more information about the event(mean= 3.94).

As for the situation of being at home while having absent family members, the average likelihood of traveling to pick up missing family members before evacuating is relatively high (mean= 4.40), while that of immediately evacuating without the missing family members is low (mean= 2).

Finally, the average value for the likelihood of adopting the response of going home to prepare for evacuation in the situation of being at work or university when the event occurs is the highest among all the suggested behavioral responses in this situation (mean= 3.64). Besides, it is higher than the likelihood of going home and not evacuating (the difference between the means equals 0.53).

Table 5.4 displays the questions stated in section three of the survey and their responses.

When asked about the evacuation mode choice, the majority of the respondents in the two samples chose to evacuate by car. Respondents said they intend to evacuate by car, maybe because they believe it will take less time to flee in a rapid-onset disaster.

Also, the majority of the respondents indicated that they either own a residence or know friends or family who own a house in a town or village outside of Beirut. Respondents were asked to select all possible locations for the destinations. The results of the two samples show that Mount Lebanon has the highest percentage, followed by South Lebanon and North Lebanon.

Further, respondents were asked to indicate if they had any other potential evacuation destination in mind. The responses to this question significantly dropped to half. Also, the respondents were asked to select all possible locations for the destinations. The results of the two samples show that evacuating outside of Lebanon has the highest percentage, followed by Mount Lebanon, South Lebanon, and North Lebanon.

Table 5.4: Summary Statistics for Questions in Section 3

Variable	Categories	Participants who work or study in Beirut (n=256)		Participants who reside in Beirut (n=162)	
		Frequency	Percentage	Frequency	Percentage
Transportation Mode for Evacuation	Car	231	90.2	144	88.9
	Walking	16	6.3	10	6.2
	Taxi/Service	1	0.4	1	0.6
	Bus or Van	1	0.4	0	0
	Motorcycle	7	2.7	7	4.3
Own a Residence or Know Friends Who Own a Residence in a Town/Village Outside Of Beirut	Yes	249	97.3	157	97
	No	7	2.7	5	3
Destinations	North Lebanon	84	32.8	49	30.2
	South Lebanon	87	34	63	39
	Mount Lebanon	140	54.7	77	47.5
	Beqaa	15	5.8	10	6.2
	Akkar	6	2.3	3	1.8
	Nabatieh	11	4.3	9	5.5
	Baalbeck/Hermel	12	4.7	7	4.3
Potential Evacuation Destinations	Yes	120	46.8	80	50.4
	No	136	53.2	82	50.6
Destinations	North Lebanon	16	6.25	10	6.2
	South Lebanon	23	9	11	6.8
	Mount Lebanon	35	13.7	20	12.3
	Beqaa	11	4.3	5	3
	Akkar	3	1.2	3	1.8
	Nabatieh	6	2.3	3	1.8
	Baalbeck/Hermel	2	0.8	1	0.6
	Outside Lebanon	38	14.8	34	21

Chapter 6

Results and Discussion

Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are implemented in order to identify and confirm the underlying relationships between the observed variables and the latent variables. Then, structural equation modeling (SEM) is utilized for estimating three models, one for the case of being at home with the family members when the event occurs, one for the case of having absent family members when the event occurs, and one for the case of being at work or university when the event occurs.

6.1 Exploratory Factor Analysis Results

Factor analysis is a technique used to represent latent concepts and for dimension reduction in human studies [141]. This study applied factor analysis to reduce multiple-item survey questions indices. The Exploratory Factor Analysis (EFA) was performed on the observed variables using the statistical software SPSS. First, the Kaiser–Meyer–Olkin (KMO) value and the significant value of the Bartlett sphericity test were obtained for the sample of respondents who reside in Beirut and the sample of respondents who work or study in Beirut. The KMO value obtained by the factor analysis for each of the two samples (KMO=0.753 for the sample of respondents who work or study in Beirut and KMO=0.741 for the sample of respondents who reside in Beirut) is above the required threshold of 0.60 - 0.70 [142]. In addition, the significant value of the Bartlett sphericity test is 0.00 for each of the two samples (less than the 0.05 threshold according to [143, 144], which indicates that the chosen observed variables are applicable for EFA. The correlations between each observable variable and each latent component are represented by rotational factor patterns (see Tables 6.1 and 6.2). In analyzing the rotational factor patterns, a variable is said to load on a given factor if the factor loading is at least 0.4 for that factor [119, 120]. Using this criterion, two factors were identified: risk perception and knowledge perception. Further, Cronbach's alpha measure was used to assess the scale reliability. According to Collier [138], an acceptable range of Cronbach's alpha is a value of 0.70 or above. Tables 6.1 and 6.2 show Chronbach's alpha measure and the total explained variance for the explored factors.

Table 6.1: Exploratory Factor Analysis: Reside in Beirut

Observable Variable	Underlying (latent) factors	
	Factor 1	Factor 2
	Risk Perception	Knowledge Perception
Likelihood of a terrorist attack or act of war to occur in Beirut in the next 12 months	0.388	
Likelihood of this event to lead to injuries for you or your family	0.846	
Likelihood of this event to create a life-threatening situation for you or your family	0.870	
Likelihood of this event to lead to severely damage or destroy your home	0.813	
Likelihood of this event event to lead to severely damage or destroy roads	0.666	
Knowledge of what safety measures to take		0.887
Having a plan in the case of this event		0.882
Knowledge of evacuation routes from your home to potential evacuation destinations		0.830
Cronbach's alpha	0.767	0.834
Total variance explained	54.7%	75.3%

* The variables are measured using a 5-point Likert scale (1:Very unlikely to 5: Very likely)

Table 6.2: Exploratory Factor Analysis: Work or Study in Beirut

Observable Variable	Underlying (latent) factors	
	Factor 1	Factor 2
	Risk Perception	Knowledge Perception
Likelihood of a terrorist attack or act of war to occur in Beirut in the next 12 months	0.402	
Likelihood of this event to lead to injuries for you or your family	0.808	
Likelihood of this event to create a life-threatening situation for you or your family	0.811	
Likelihood of this event to lead to severely damage or destroy your home	0.712	
Likelihood of this event event to lead to severely damage or destroy roads	0.561	
Knowledge of what safety measures to take		0.792
Having a plan in the case of this event		0.736
Knowledge of evacuation routes from your home to potential evacuation destinations		0.639
Cronbach's alpha	0.76	0.797
Total variance explained	53.5 %	71.3%

* The variables are measured using a 5-point Likert scale (1:Very unlikely to 5: Very likely)

6.2 Models Development and Analysis

6.2.1 *Measurement Model Results*

The measurement model for each of the two samples was validated by performing first-order confirmatory factor analysis (CFA) to examine how well the questionnaire items represent the construct. The measurement model includes the two constructs that resulted from the EFA which are risk perception and knowledge perception. The assessment of the measurement model mainly includes testing the reliability and validity of the explored latent variables.

For assessing reliability, Composite Reliability (C.R.) was adopted. The calculation of the C.R. is based on factor loadings from the CFA. According to [145, 138], the composite reliability should be higher than 0.70. The results presented in Tables 6.3 and 6.4 show that all C.R. values satisfy the previously recommended threshold value.

The validity tests of the measurement model are divided into two types: convergent validity tests and discriminant validity tests. The convergent validity test determines whether all the indicators for a construct measure the same thing. The discriminant validity determines whether the construct is distinct and different from other prospective constructs of interest.

For the test of convergent validity of the measurement model, Average Variance Extracted (AVE) was used. According to Collier [138], the AVE scores should be higher than the value of 0.50. Tables 6.3 and 6.4 show that all values of the AVE of the latent variables are higher than 0.5.

For the evaluation of the test of discriminant validity, the Fornel-Larcker criterion was adopted. The square root of AVE in each latent variable and other correlation values were compared. The square root of AVE in each latent variable

Table 6.3: Standardized Factor Loading, Composite Reliability, and Average Variance: Reside in Beirut

Constructs	Standarized Factor Loading	C.R.	AVE
Risk Perception		0.83	0.53
Likelihood of a terrorist attack or act of war to occur in Beirut in the next 12 months	0.323		
Likelihood of this event to lead to injuries for you or your family	0.866		
Likelihood of this event to create a life-threatening situation for you or your family	0.921		
Likelihood of this event to severely damage or destroy your home	0.756		
Likelihood of this event to severely damage or destroy roads	0.61		
Knowledge Perception		0.86	0.68
Knowledge of what safety measures to take	0.873		
Having a plan in the case of this event	0.859		
Knowledge of evacuation routes from home to potential evacuation destinations	0.753		

Table 6.4: Standardized Factor Loading, Composite Reliability, and Average Variance: Work or Study in Beirut

Constructs	Standarized Factor Loading	C.R.	AVE
Risk Perception		0.83	0.51
Likelihood of a terrorist attack or act of war to occur in Beirut in the next 12 months	0.377		
Likelihood of this event to lead to injuries for you or your family	0.879		
Likelihood of this event to create a life-threatening situation for you or your family	0.913		
Likelihood of this event to severely damage or destroy your home	0.715		
Likelihood of this event to severely damage or destroy roads	0.559		
Knowledge Perception		0.83	0.63
Knowledge of what safety measures to take	0.78		
Having a plan in the case of this event	0.838		
Knowledge of evacuation routes from home to potential evacuation destinations	0.765		

is compared with the correlation value; if the value is larger than the correlation values, the discriminant validity is accepted [146]. As shown in Tables 6.5 and 6.6, the Fornel-Larcker criteria in diagonals are higher than the correlation values in related off-diagonals. The square root of the risk perception factor's AVE is larger than the correlation values in the column of the risk perception factor, and it is also larger than those in the row of the risk perception factor. The results indicate that discriminant validity is well established.

Table 6.5: Discriminant Validity Assessment (Fornell-Larcker Test): Reside in Beirut

Latent Variables	Knowledge Perception	Risk Perception
Knowledge Perception	0.830	
Risk Perception	-0.056	0.728

Notes: Diagonals represent the square root of the AVE; the off diagonals represent the correlations.

Table 6.6: Discriminant Validity Assessment (Fornell-Larcker Test): Work or Study in Beirut

Latent Variables	Knowledge Perception	Risk Perception
Knowledge Perception	0.794	
Risk Perception	-0.215	0.717

Notes: Diagonals represent the square root of the AVE; the off diagonals represent the correlations.

6.2.2 *Structural Equation Models Development*

After developing a measurement model for each of the two samples, SEM was utilized to test three path models structured according to the PADM. The three developed SEM models were for the following situations when the human-made hazard occurs: **(1)** at home with all family members, **(2)** some family members missing, and **(3)** at work or university.

The three SEM models were estimated with the package lavaan (version 0.6-10) [147] in R (version 4.1.2), a programming language for statistical computing and visualization.

Correlations between any two latent variables or between any two intended evacuation behavior variables were permitted. The identification of the models was ensured by normalizing the variances of the latent variables to one. Furthermore, before being used in the analysis, all independent categorical variables were dummy coded. The diagonally weighted least squares robust estimation technique was used to address the non-normality of the collected data. The SEM was then iteratively improved by eliminating insignificant factors and variables. Examples of removed factors are social cues, warning messages, and information sources and preferences. Moreover, examples of removed demographic variables include car ownership, homeownership, years of residence, occupational status, education, and household size.

Figures 6.1, 6.2, and 6.3 display the three final models with the estimates and the respective p-values (values between parentheses). For clarity, neither the variances nor the threshold model is depicted in Figures 6.1, 6.2, and 6.3.

Then the mediation analysis was conducted for models one and three to determine whether the latent variables mediate the effect of the demographic and situational variables on the intended evacuation behavior variables. A direct path is drawn from the situational variables to the intended evacuation behavior variables to determine the type of mediation present in the analysis. The mediation analyses results are displayed in Tables 6.8 and 6.9.

6.2.3 *Structural Equation Models Results and Discussion*

6.2.3.1. *Goodness-Of-Fit Measures*

The model fit indices presented in Figures 6.1, 6.2, and 6.3 suggest a good or acceptable fit. For each model, the CFI and TLI values are greater than 0.95, indicating a good fit. The relative chi-squared values for the three models are acceptable for Ulman's suggested relative chi-squared criterion of 2 [133]. The three models have an SRMR value between 0.05 and 0.09, which indicates an adequate fit. Regarding the RMSEA, it has a value of less than 0.05 in model three, which indicates a good model fit. Models one and two both have RMSEA values greater than 0.05. However, their RMSEA values are still less than 0.08, which indicates a reasonable model-data fit. The inclusion of additional variables in model three may explain why it has better fit indices than models one and two.

6.2.3.2. *Measurement Model Estimation Results*

Regarding the measurement relations shown in Figures 6.1, 6.2, and 6.3, almost all of their factor loading are higher than 0.5 and they are significant at a level

Table 6.7: Summary of hypotheses and results.

				Model 1	Model 2	Model 3
H1	Signs of destruction in the surrounding environment	-	Risk perception	Supported	Supported	Supported
H2	Social cues	-	Risk perception	Rejected	Rejected	Rejected
H3	Demographic characteristics	-	Risk perception	Supported	Supported	Supported
H4	Strong government disaster response and government's recommended course of action	-	Risk perception	Rejected	Rejected	Partially Supported
H5	Sources of information and preference	-	Risk perception	Rejected	Rejected	Rejected
H6	Demographic characteristics	-	Knowledge perception	Rejected	Rejected	Supported
H7	Risk perception	-	Behavioral response	Partially Supported	Rejected	Partially Supported
H8	Knowledge perception	-	Behavioral response	Partially Supported	Partially Supported	Partially Supported
H9	Ownership of a residence or knowledge of friends/family who own a residence in a town/village outside of Beirut, Lebanon	-	Behavioral response	Rejected	Rejected	Rejected
H10	Knowledge of evacuation destination (inside or outside Lebanon)	-	Behavioral response	Supported	Rejected	Rejected

of significance $\alpha = 0.01$.

6.2.3.3. *General Overview of the Three Developed Structural Equation Models*

As for the path model, the hypotheses stated in Chapter 3 were tested for each model. The standardized estimates of the coefficients for the paths between the variables were examined for their significance. A summary of the results of the three models is presented in Table 6.7.

Common results in the three models will be discussed before presenting the interpretation for each model in a separate section.

First, H1 is supported in the three models as the results show that signs of destruction in the surrounding environment have a significant positive effect (Models 1 and 2: 0.242, $p \leq 0.05$; Model 3: 0.185, $p \leq 0.05$;) on risk perception. This result indicates that the signs of destruction in the surrounding environment affect risk perception. This relationship is consistent with the PADM framework, where an individual's observation of disaster cues triggers threat perceptions [1].

Second, H2 is not supported in the three models because the estimates for the coefficients of the path between the behavior (evacuating or not evacuating) of loved ones and neighbors and the risk perception are not significant. This result indicates that the behavior of loved ones and neighbors does not affect risk perception. Although the impact of social cues on threat perception is one of the main assumptions in the PADM [1], this study couldn't support it. Moreover, studies on factors impacting evacuation decisions showed that social cues influence them [35, 36, 110]. This relationship is also not supported in this study. The inconsistency with the PADM framework and previous studies may be because this study was conducted during the COVID-19 pandemic, and it is difficult to capture the impact of social influence on evacuation decision-making within the dual emergency context (pandemic-concurrent human-made disaster).

Third, H3 is supported in the three models. Among various demographic variables tested, gender seems to have a significant effect on risk perception (Models 1: 0.475, $p \leq 0.05$; Model 2: 0.481, $p \leq 0.01$; Model 3: 0.542, $p \leq 0.01$;). Specifically, females have a higher risk perception than males. Besides, this result is in line with the finding of the World Trade Center (WTC) evacuation study conducted by Sherman et al. that being female was associated with increased perceived risk [76]. On the other hand, health condition seems to have a significant positive ($0.397, p \leq 0.05$) effect on risk perception only in Model 3 for being at work or university when the event occurs. In other words, respondents that suffer or have any of their family members suffer from a bad health condition have a higher risk perception than respondents that don't suffer or any of their family members don't suffer from a bad health condition. This result is in line with the finding of Bhuiya and Shao [148] that disability is significantly related to risk perception.

Fourth, H4 and H5 are not supported in the three models. The estimates of the coefficients for the path between each of the strong governmental disaster responses and the recommended course of action by the government and risk perception are not significant. That is, none of the government responses influences the respondents' risk perception. Besides, estimates between the sources of information and risk perception are not significant. This means that preference for the sources of information doesn't influence risk perception. These findings are inconsistent with the PADM framework [1] and previous studies. Obtained information influences risk perception, according to the findings of a study conducted by Kuligowski and Mileti [149]. Besides, Drabek [150] found that higher perceived risk is associated with warning messages implying that evacuation is mandatory. Other studies examined the effects of different types of information sources on the evacuation decision [35, 151] and found that there was a significant relationship between them. Although the influence of the government's evacuation recommendations is supported by several studies, this result is not supported by the current study.

Fifth, H6 is not supported in Models 1 and 2. Among various demographic variables tested, none seemed to have a significant effect on knowledge perception in Models 1 and 2. On the other hand, gender, household monthly income, and health condition seem to have a significant effect on knowledge perception in Model 3. The sign of the estimate on the link between female and knowledge perception is negative ($-0.431, p \leq 0.01$), which means that males have higher knowledge perception than females. The result is in line with a review of research conducted by Lindell and Perry [152] that showed that gender is associated with individual preparedness for natural disasters. Moreover, the sign of the estimate of the link between health condition and knowledge perception is negative ($-0.371, p \leq 0.05$). This result means that respondents that don't suffer or any of their family members don't suffer from a bad health condition have a higher knowledge perception than respondents that suffer or any of their family members suffer from a bad health condition. This result is not in line with the previous finding of Eisenman et al. [153] that people with disabilities are more likely than people without disabilities to have an emergency plan in case a terrorist attack occurred in Los Angeles County. As for the estimate of the link between household monthly income and knowledge perception, its sign is positive ($+0.016, p \leq 0.1$). This result means that the higher the household monthly income of the respondents, the greater their knowledge perception.

The remaining hypotheses (H7 to H12) will be discussed in the following sections for each model separately, as the intended evacuation behaviors studied in each situation are different than in the other.

6.2.3.3.1. *Model One for the Situation of Being at Home With All Family Members*

H7 and H8 test the effect of cognitive factors on the intended evacuation behaviors. These two hypotheses are partially supported by Model 1. The results show that each of risk perception ($0.286, p \leq 0.01$) and knowledge perception ($0.203, p \leq 0.05$) has a significant positive effect on the intended behavior of beginning evacuation preparations. This result means that cognitive factors influence the intended behavior of beginning evacuation preparations. Moreover, this result is in line with the findings of previous studies [154, 88] and the PADM framework [1], which indicate that risk perception and knowledge perception affect evacuation decisions. On the other hand, neither of the risk perception and knowledge perception seemed to influence the intended evacuation behavior of immediately evacuating. The reason for obtaining such a result could be explained by the indirect influence of the presence of all family members, which can lead to the beginning of evacuation preparations before evacuation. This reason is supported by the positive and significant correlation ($0.253, p \leq 0.01$)

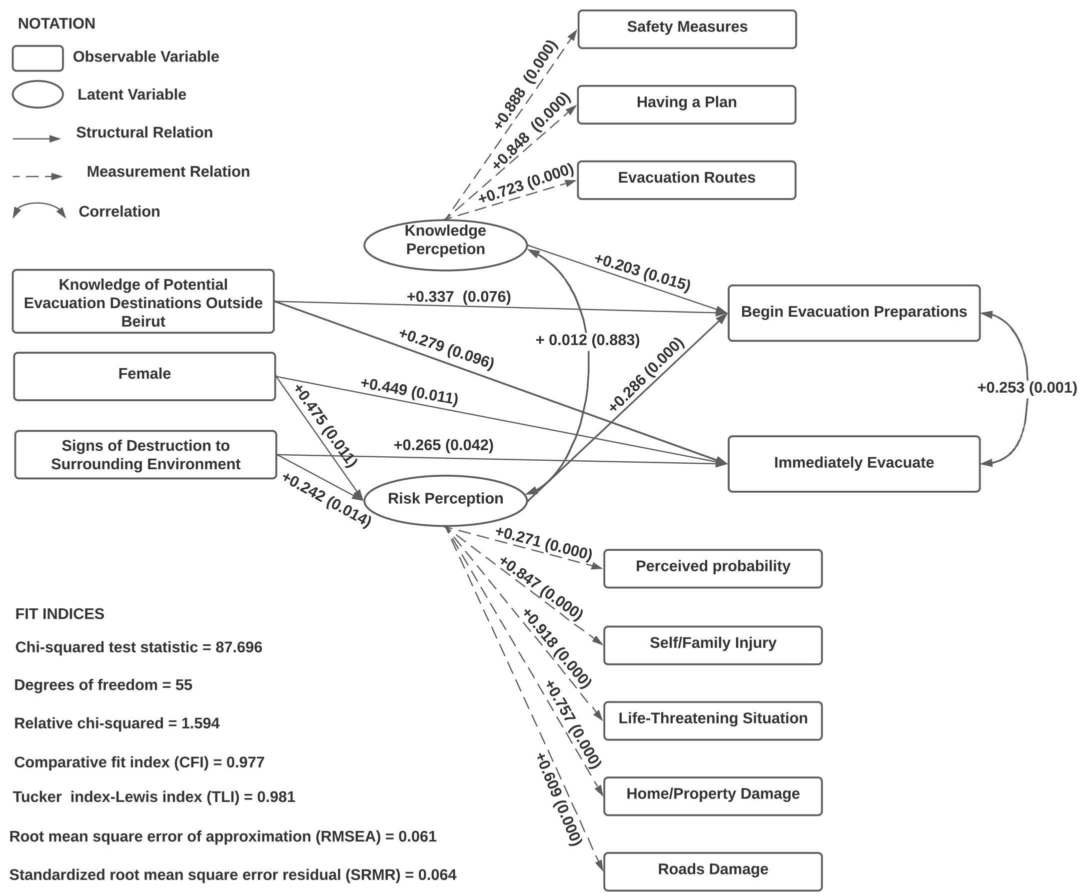

Figure 6.1: SEM: At Home with All Family Members.

between the intended behavior of evacuating immediately and beginning evacuation preparations shown in Figure 6.1.

Regarding the hypotheses testing the effect of evacuation facilitators on the intended evacuation behaviors, H9 is unsupported while H10 is supported. The results show that the ownership of a residence or knowledge of friends or family who own a residence in a town or village outside of Beirut, Lebanon, doesn't influence the intended evacuation behaviors. On the other hand, the results show that the knowledge of an evacuation destination (inside or outside Beirut) has a positive significant effect on each of the intended behaviors of beginning evacuation preparations ($0.337, p \leq 0.1$)and leaving immediately ($0.279, p \leq 0.1$).

This result means that knowledge of evacuation destinations (inside or outside Beirut) influences intended evacuation behaviors in the case of being at home with all family members when the event occurs. This result is in line with the PADM framework [1], which assumes that some conditions facilitate or impede intended actions.

A mediation analysis was conducted to test H11, which states that risk perception plays the role of the mediator between demographic and situational variables and the intended evacuation behavior variables. The results shown in Table 6.8 indicate that being a female and observing signs of destruction in the surrounding environment has a significant indirect effect on the intended behavior of beginning evacuation preparations through risk perception. Also, the results show that observing signs of destruction in the surrounding environment have a significant direct effect on the intended behavior of beginning evacuation preparations. This implies that the influence of observing signs of destruction in the surrounding environment on the intended behavior of beginning evacuation preparations is partially mediated through risk perception. On the other hand, the results show that being a female does not have a significant direct effect on the behavior of beginning evacuation preparations. This implies that the influence of being a female on the intended behavior of beginning evacuation preparations is fully mediated through risk perception.

Table 6.8: Test of Mediation: Model One

Relationships	Direct Effect (Est./Sig)	Indirect Effect (Est./Sig)	Total Effect (Est./Sig)	Mediation Effect
Female → Risk Perception →Begin Evacuation Preparations	0.001/NS	0.136/**	0.136/NS	Full Mediation
Signs of Destruction of the Surrounding Environment →Risk Perception → Begin Evacuation Preparations	0.355/***	0.069/**	0.424/***	Partial Mediation

** p $\leq$ 0.01; *p $\leq$ 0.05; NS-Not Significant

Regarding H12, it was not examined in this model because knowledge perception is not influenced by gender and signs of destruction in the surrounding environment variables. Therefore, knowledge perception doesn't have a mediator effect in Model 1.

Finally, the results show that each of the female $(0.449, p \leq 0.05)$ and observing signs of destruction in the surrounding environment $(0.265, p \leq 0.05)$ variables has a positive and significant effect on the intended behavior of immediately evacuating. In other words, females are more likely than males to evacuate immediately. Also, observing signs of destruction in the surrounding environment influences the intended behavior of beginning evacuation preparations.

Moreover, the latent variables, risk perception, and knowledge perception are not correlated. The intended evacuation behaviors, on the other hand, are positively correlated $(0.253, p \leq 0.01)$.

6.2.3.3.2. *Model Two for the Situation of Having Absent Family Members*

H7 is not supported by Model 2. The results show that risk perception doesn't influence the intended evacuation behaviors in the situation of having absent family members when the event occurs.

H8 is partially supported. The results show that knowledge perception has a significant positive effect $(0.155, p \leq 0.1)$ on the intended evacuation behavior of traveling to pick up missing family members before evacuating. However, it doesn't influence the intended evacuation behavior of immediately evacuating without the missing family members. This result is in line with the finding of one of the very few studies [16] focusing on the evacuation behavior of people during no-notice emergency events, which found that family members are most probably located at different locations during the daytime, and parents make additional

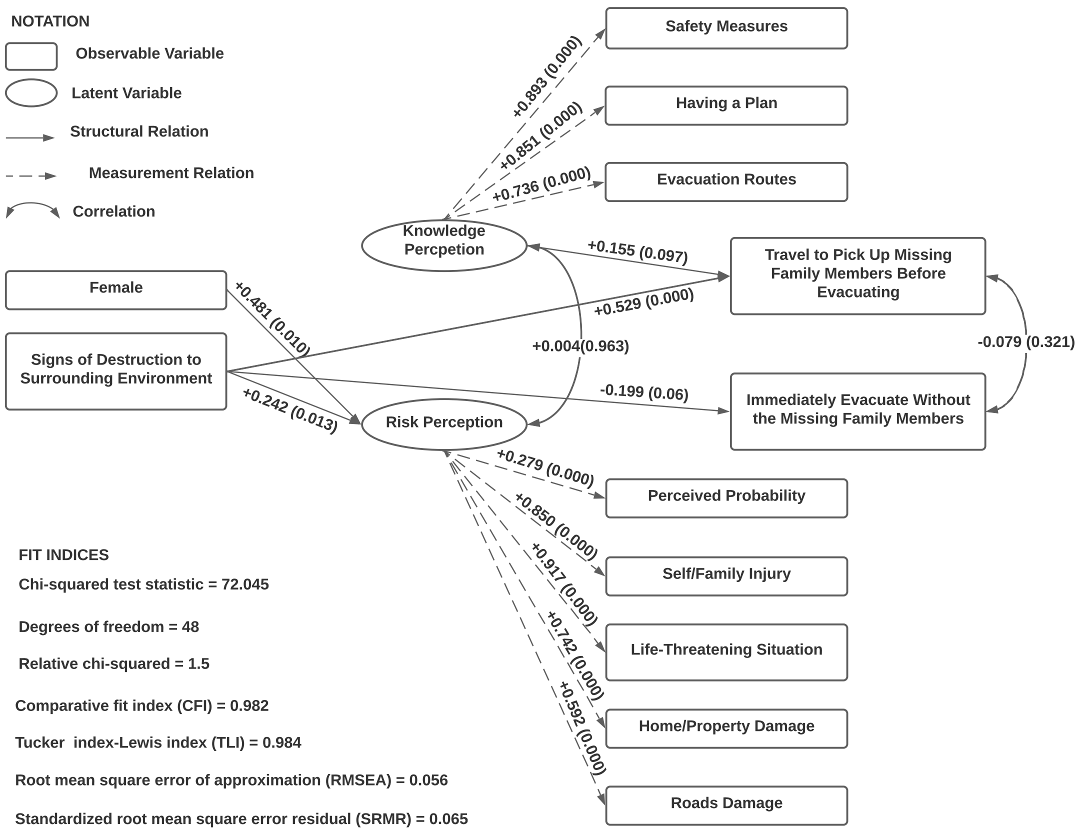

Figure 6.2: SEM: Having Absent Family Members.

trips to pick up their children.

Regarding H9 and H10, they are unsupported by Model 2. The results show that the ownership of a residence or knowledge of friends or family who own a residence in a town or village outside of Beirut, Lebanon, doesn't influence the intended evacuation behaviors. Besides, knowledge of evacuation destinations (inside or outside Beirut) doesn't influence intended evacuation behaviors.

H11 and H12 weren't examined in this model. That is because risk perception doesn't influence the intended evacuation behaviors in Model 2. Besides, knowledge perception is not influenced by gender and signs of destruction in the surrounding environment. Therefore, risk perception and knowledge perception don't have a mediator effect in this model.

Finally, the results show that observing signs of destruction in the surrounding environment variables has a positive and significant effect $(0.529, p \leq 0.01)$ on the intended behavior of traveling to pick up missing family members before evacuating. On the other hand, it has a negative and significant effect $(-0.199, p \leq 0.1)$ on the intended behavior of evacuating immediately without the missing family members. In other words, observing signs of destruction in the surrounding environment encourages the adoption of the behavior of traveling to pick up missing family members, whereas it discourages evacuating immediately without them.

Moreover, the latent variables, risk perception, and knowledge perception are not correlated. The intended evacuation behaviors also are not correlated.

6.2.3.3.3. *Model Three for the Situation of Being at Work or University*

H7 is supported by Model 3. The results show that risk perception has a significant positive effect on the intended evacuation behaviors of going home to prepare for evacuation $(0.184, p \leq 0.01)$ and immediately evacuating from the work or university location $(0.115, p \leq 0.1)$. In other words, the higher the risk perception of the respondents, the more likely they are to evacuate immediately or leave home to prepare for evacuation. This result is in line with the findings of previous studies [154, 88] and the PADM framework [1], which indicate that risk perception affects evacuation decisions.

H8, on the other hand, is partially supported. The results show that knowledge perception has a significant positive effect $(0.18, p \leq 0.05)$ on the intended evacuation behavior of going home to prepare for evacuation. This result means that the higher the knowledge perception of the respondents, the more likely they are to go home to prepare for evacuation. Besides, this result is in line with the

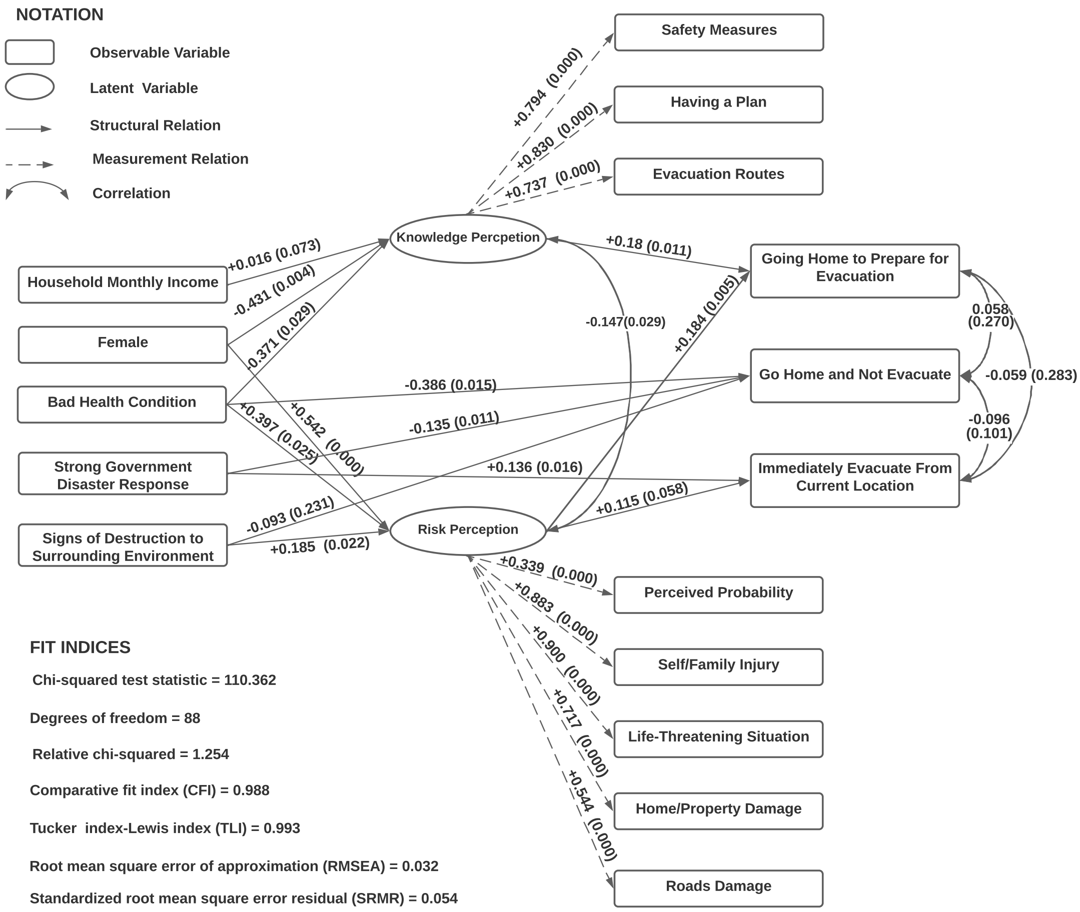

Figure 6.3: SEM: At Work or University.

finding of Buylova et al. [88], that knowledge perception affects behavioral intentions. On the other hand, knowledge perception doesn't influence the intended evacuation behavior of going home and not evacuating or evacuating immediately from the work or university location.

Regarding H9 and H10, they are unsupported by Model 3. The results show that the ownership of a residence or knowledge of friends or family who own a residence in a town or village outside of Beirut, Lebanon, doesn't influence the intended evacuation behaviors. Besides, knowledge of evacuation destinations (inside or outside Beirut) doesn't influence intended evacuation behaviors.

A mediation analysis was conducted to test H11 and H12, which state that each risk perception and knowledge perception plays the role of the mediator between demographic and situational variables and the intended evacuation behavior variables.

The results shown in Table 6.9 indicate that observing signs of destruction in the surrounding environment has a significant indirect effect on the intended behavior of going home to prepare for evacuation through risk perception. Also, the results show that observing signs of destruction in the surrounding environment has a significant direct effect on the intended behavior of going home to prepare for evacuation. This implies that the influence of observing signs of destruction in the surrounding environment on the intended behavior of beginning evacuation preparations is partially mediated through risk perception.

The results of the parallel mediation show that gender has a significant indirect effect on the intended behavior of going home to prepare for evacuation through two mediators: risk perception and knowledge perception. Moreover, the results indicate that gender doesn't have a direct effect on the intended behavior of going home to prepare for evacuation. This result implies that the influence of gender on the intended behavior of going home to prepare for evacuation is partially mediated through the two mediators: risk perception and knowledge perception.

On the other hand, the results of the parallel mediation show that health condition has an indirect effect on the intended behavior of going home to prepare for evacuation only through one mediator, which is risk perception. Besides, the results indicate that health conditions don't have a direct effect on the behavior of beginning evacuation preparations. This result implies that the influence of health conditions on the intended behavior of going home to prepare for evacuation is fully mediated through risk perception.

Finally, the results show that each of the health conditions $(-0.386, p \leq 0.05)$

Table 6.9: Test of Mediation: Model Three

Relationships **One Mediator**	Direct Effect (Est./Sig)	Indirect Effect (Est./Sig)	Total Effect (Est./Sig)	Mediation Effect
Household Monthly Income → Knowledge Perception → Go Home to Prepare for Evacuation	0.005/NS	0.003/NS	0.008/NS	No Mediation
Female→Risk Perception → Immediately Evacuate from Current Location	0.075/NS	0.063/NS	0.138/NS	No Mediation
Bad Health Condition → Risk Perception → Immediately Evacuate from Current Location	0.282/*	0.046/NS	0.328/**	No Mediation
Signs of Destruction in the Surrounding Environment → Risk Perception → Go Home to Prepare for Evacuation	0.217/**	0.034/*	0.251/***	Partial Mediation
Signs of Destruction in the Surrounding Environment → Risk Perception → Immediately Evacuate from Current Location	0.102/NS	0.021/NS	0.123/NS	No Mediation
Two Mediators				
Female → Knowledge Perception → Go Home to Prepare for Evacuation	0.145/NS	-0.078/**	0.167/NS	Full Mediation Through Two Mediators
Female → Risk Perception → Go Home to Prepare for Evacuation		0.1/**		
Bad Health Condition → Knowledge Perception → Go Home to Prepare for Evacuation	0.112/NS	-0.067/NS	0.118/NS	Full Mediation Through One Mediator
Bad Health Condition → Risk Perception → Go Home to Prepare for Evacuation		0.073/*		

*** p 0.01; **p,0.05; *p 0.1; NS-Not Significant

and observing a strong government disaster response $(-0.135, p \leq 0.05)$ has a negative and significant effect on the intended behavior of going home and not evacuating. In other words, respondents that don't suffer or any of their family members that don't suffer from a bad health condition, are more likely to go home and not evacuate than respondents that suffer or any of their family members suffer from a bad health condition. Moreover, it is unlikely for respondents to go home and not evacuate when observing a strong government disaster response. On the other hand, the results show that observing a strong government disaster response has a positive and significant $(+0.136, p \leq 0.05)$ effect on the intended behavior of immediately evacuating from a work or university location. This result implies that it is likely for respondents to immediately evacuate from their current location when observing a strong government disaster response.

Moreover, the latent variables, risk perception, and knowledge perception are negatively correlated $(-0.147, p \leq 0.029)$. The intended evacuation behaviors, on the other hand, are not correlated.

Chapter 7

Conclusion and Recommendations

This chapter concludes the thesis. It focuses on the study's key findings and explains the study's implications. Then the study limitations are stated, along with future research suggestions.

7.1 Summary of Findings

While successful evacuation from disasters with enough lead warning time is difficult to execute due to the required level of coordination among agencies and jurisdictions, this problem is exacerbated during the evacuation from disasters with less lead warning time. This necessitates an in-depth investigation of people's evacuation behaviors as well as the identification of the most influential factors in their evacuation planning process to develop policy-sensitive pre-disaster plans for such events. Although evacuation behavior during disasters with enough lead warning time has been extensively explored in the literature, evacuation behavior during disasters with less lead warning time has not yet been adequately investigated.

This study contributes to the literature by focusing on the predictors of evacuation behavior in the case of a hypothetical human-made disaster (terrorist attack or act of war) in Beirut using a web-based survey conducted in the Municipality of Beirut Area and its surroundings. Given the vulnerability of the Lebanese population to both natural and human-made disasters and the catastrophic circumstances of the recent explosion of Beirut Port on August 4, 2020, there is a vital need for pre-disaster preparation to mitigate potential damage from such catastrophes. Using the PADM as a guide to questionnaire design, this study captured the impact of several factors on the decision-making process simultaneously: (1) the impact of situational and social factors, as well as demographic characteristics on risk perception; (2) the impact of demographic characteristics on knowledge perception; (3) the impact of cognitive factors on the intended evacuation behavior; and (4) the mediation effect of cognitive factors.

Using the results of the conducted survey, three structural equation models were developed for three situations. The first model is for being at home with all family members; the second model is for having absent family members, and the third model is for being at work or university when the event occurs.

The findings of this study show that the PADM framework is relevant to explaining evacuation behavior intentions prior to a human-made disaster incident. The Main insights that apply to the three models are that cognitive factors like risk perception and knowledge perception are important determinants of evacuation behavior.

Key results indicate that show that risk perception triggers the intended behavior of evacuating immediately in the situation of being at work or university. Also, risk perception triggers the intended behavior of beginning evacuation preparation in the situation of being at home with all family members and going home to prepare for evacuation in the situation of being at work or university. On the other hand, results indicate that knowledge perception doesn't trigger the intended behavior of evacuating immediately in the three studied situations. Knowledge perception only triggers the intended behavior of beginning evacuation preparation in the situation of being at home with all family members and going home to prepare for evacuation in the situation of being at work or university. Also, knowledge perception triggers the intended behavior of traveling to pick up missing family members before evacuating in the case of having absent family members when the incident occurs.

As for signs of destruction in the surrounding environment and gender, results indicate that they trigger risk perception in the three studied situations. Also, demographic characteristics, health condition , and household monthly influence cognitive factors in the situation of being at work or university when the event occurs. On the other hand, results indicate that the government's recommended course of action, social cues, and channel access and preference don't trigger risk perception or directly influence the intended evacuation behaviors in the three situations. Moreover, observing a strong government disaster response doesn't trigger risk perception in the three situations. It only influences the intentions of the respondent to adopt the behavior of immediately evacuating and discourages them from adopting the behavior of going home and not evacuating.

Further, results indicate that ownership of a residence or knowledge of friends or family who own a residence in a town or village outside of Beirut, Lebanon, doesn't influence the intended evacuation behaviors in any of the three situations. However, knowledge of evacuation destinations (inside or outside Beirut) only influences the intended behaviors of immediately evacuating or beginning evacuation preparations for the situation of being at home with all family members when the event occurs.

Finally, mediation analysis results contribute to the PADM framework by indicating that demographic characteristics (gender and health condition) and signs of destruction in the surrounding environment indirectly influence evacuation behavior through cognitive factors.

7.2 Study Implications

This study is an important step towards understanding and modeling the factors that affect the evacuation behavior intention of the Municipal Beirut Area residents and its surroundings population. The absence of a relationship between knowledge perception and intended behavior of immediate evacuation in the three studied situations suggests a vital need for adopting approaches that promote preparedness and foster resilience among individuals and communities. Previous studies [155, 156, 157] showed that preparedness might contribute to an individual's resilience to trauma. Besides, campaigns that raise awareness of potential threats could help encourage individual preparedness and planning [83]. Moreover, preparedness might help discourage terrorists from conducting an attack because they believe that the attack may be unsuccessful due to the high preparedness level [153].

This study is also important for understanding human-made disasters (terrorist attack or act of war) evacuation logistics, such as evacuation mode choice, evacuation route, and evacuation destination. The majority of the respondents intend to choose the car (89.5%) as their evacuation mode. Respondents said they intend to evacuate by car because they believe it will take less time to flee in a rapid-onset disaster. However, due to the increased likelihood of traffic congestion, delays, and drivers' unsafe behavior as a result of worry, aggression, stress, and exhaustion, this estimate may be wrong. Emergency managers and cities can develop a simulation based on the evacuation mode choice distribution to study traffic delays during evacuations and customize programs to inform citizens about the best mode of evacuation and other logistics.

Moreover, the results show that when faced with the situation of having absent family members, respondents intend to travel to pick up the missing family members before evacuating. Also, results show that, in the case of being at work or university, respondents intend to go home to prepare for evacuation. These intended evacuation behaviors indicate the likelihood of delays in the case of a rapid-onset disaster. The issue of households' child pick-up behavior during no-notice emergency events was addressed by Liu et al. [16]. The findings of their study revealed that during the day, family members are most likely in various areas, and parents make additional trips to pick up their children, which, if ignored, can lead to an underestimation of total network trips.

Further, the descriptive statistics results of the ranking question (1 to 4) related to the preference for the source of information about the incident show that the friends/family calls rank in the first place, the social media rank in the second place, the private TV news channels rank in the third place, and the official government warning rank in the fourth place. This highlights the unreliability of official government warnings in such incidents. According to a study conducted by Sadri et al. [151], the reliability of different types of information sources, such as radio, television, social media, and the Internet, has a significant impact on evacuation decisions. Therefore, emergency planners should consider the channel access and preference when spreading information about disasters. For instance, a study by Kaufman et al. [158] showed that many citizens who did not have access to traditional forms of information (such as television) were able to receive information via social media on their smartphones.

As for the result obtained by this study that the government's recommended course of action (i.e. either go or no go decision) doesn't trigger risk perception nor influence the evacuation behavior in the three studied situations, it is not in line with several previous studies [15, 35, 151, 159] that indicated the significant influence of the government evacuation recommendation on the evacuation decision.

Moreover, descriptive statics results show that around eighty percent of the respondents are not very confident about knowing the government's emergency evacuation strategy and that none of the respondents are very confident about it. This result proves the urgent need for disaster risk management in Lebanon.

7.3 Study Limitations

There are three main limitations to this study. First, the target population of the survey conducted for this study was mainly focused on the younger generation of licensed drivers that work, study, and/or reside in the Municipal Beirut Area and its surroundings. Thus, the results of this study are specific to the segment of the population aged between eighteen and twenty-nine and those who are university students. Second, the number of observations in the sample of participants who reside in the Municipal Beirut Area and its surroundings is small. These limitations are due, in part, to the use of convenience-based sampling, which is justified for evacuation research [160] and COVID-19 travel behavior studies [161] due to safety concerns. Third, the data for this study was collected during the

COVID-19 pandemic, and this might have influenced the results of this study. That is because the survey did not capture the impact of social influence on evacuation decision-making within the dual emergency context (pandemic-concurrent human-made disaster). The lack of such information in the used data is a limitation of this study, therefore integrating such aspects could be a future research area.

7.4 Future Research

Several future research directions for this study are possible. First, given the study's limitation that it is primarily representative of students' perceptions, a follow-up study could investigate the perceptions of other population groups besides students. Second, given the vulnerability of Lebanon to natural hazards and specifically disastrous earthquakes [162], further research is recommended on risk perception and factors that influence evacuation behavior in such types of hazards. Third, collecting a revealed preference dataset for Beirut's port explosion for model validation is an important future step of this research. Finally, evolving technologies such as in-vehicle advanced ITS applications and variable message signs (VMS) provide decision support and guidance for drivers in an emergency evacuation [163]. For instance, a study by Dong [164] showed that in-vehicle guidance systems have a significant impact on alleviating congestion in urban road networks. Besides, several studies highlighted the importance of in-vehicle, VANET-based disaster routing guidance [165, 166, 167]. Results showed the significance of these systems in reducing mortality rates and maintaining a balanced traffic flow over the traffic network. Therefore, conducting a driving simulator study to examine the drivers' compliance with intelligent information dissemination systems could be a fruitful direction for future studies.

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