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Considering Disaster Volunteer Behavior and the Work Environment in Managerial Decision Making

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CONSIDERING DISASTER VOLUNTEER BEHAVIOR AND THE WORK ENVIRONMENT IN MANAGERIAL DECISION MAKING

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ABSTRACT

Over the last two decades, large-scale disaster events have significantly increased in frequency and intensity, causing tremendous loss of lives and property. A large number of relief organizations rely on their volunteers to respond to many disasters around the globe, serving people and communities in need. While their contributions are priceless, turnover among disaster volunteers has become a significant problem for these relief organizations. Work environment factors, such as volunteers being mismatched with tasks, unsuitable workloads, and conflict within groups of volunteers may give rise to turnover intentions, which may in turn lead to actual turnover. The link between work environment factors and volunteer turnover intentions in these situations has not yet received considerable attention in terms of quantitative research. Therefore, the purpose of this dissertation is to develop quantitative models that consider the factors that may cause turnover or turnover intentions. The goal of these models is to help decision makers for non-governmental organizations (NGOs) better manage their disaster volunteers during relief efforts, with the aim of satisfying community needs and improving volunteer retention rates.

The first study addresses a gap in volunteer staff planning and scheduling where volunteer training is first presented, with volunteer turnover represented as a percentage of volunteer–task mismatch. We have developed a mixed-integer programming model for assigning optimal volunteer assignments based on a range of possible short- and long-term community need scenarios. The objective is to minimize the costs of unmet community needs, volunteer attrition due to mismatch assignments, and volunteer

expenses. Under different demand scenarios, the optimum solution of volunteer assignment is to allow unskilled volunteers to start training early so that they can help skilled volunteers when a peak of long-term skilled task demand is expected.

The second study investigates the effects of work environment factors on the satisfaction level and turnover intentions of disaster volunteers. Using an online survey, data from 386 disaster volunteers are collected and analyzed. Confirmatory factor analysis (CFA) and structural equation modeling are used to test the measurement model and answer research questions focused on volunteer behavior. After assessing and confirming the measurement model, we use the structural model to test the hypotheses and provide prediction equations. Job-fit, training, workload, volunteer group, and supervisor are the key work environment factors considered in this study. The findings suggest that these work environment factors have a positive significant relationship with satisfaction and a negative significant relationship with turnover intentions.

The last study focuses on developing a simulation modeling approach that considers a volunteer's satisfaction and turnover intentions in relation to management decisions of an NGO during a relief event. We use a survey to gather information from disaster volunteer managers about how they manage their volunteer teams and use this information and the findings from the second study to model a realistic relief event. We develop a hybrid simulation model, agent based and discrete event (AB-DE), that handles volunteer task and location assignments, as well as workload. Using data analysis from the surveys, we also introduce a group conflict variable within the simulation model. We evaluate the impact of different management decisions on unmet community needs, as

well as on volunteer satisfaction and turnover intentions from the organization. This study uses a numerical example based on the survey data. Considering the scenario in which disaster volunteer managers do not assign heavy workload to disaster volunteers, the results of this study suggest that as a surplus of available volunteers' increases, the overall satisfaction increases while the turnover intention decreases due to dissatisfaction with a non-essential workload as well as from group conflict. In contrast, when the number of volunteers is less than what is needed, disaster volunteers' satisfaction and turnover intentions were not affected even if there is high group conflict due to the positive effect of the workload that offsets the negative impact of the group conflict.

DEDICATION

This dissertation is dedicated to my loving parents, my brothers and sisters for their endless love, support, and prayers, to my beautiful and wonderful wife, Sumaia, for being supportive, encouraging, loving, and patient during this long journey, to my lovely kids Anees and Elias. You have brought the most joy to my life. I am grateful to have you all in my life.

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CHAPTER ONE

INTRODUCTION

Every year, natural and manmade disasters affect a huge number of lives and cause massive destruction of property. According to Van Wassenhove (2006), on average, 500 large-scale disasters, natural and manmade, kill about 75,000 people and affect a population of 200 million every year. The number of weather- and climate-related disasters has increased more than twofold over the past 40 years, accounting for 3,017 events from 1976–1995 and up to 6,392 events from 1996–2015 (Centre for Research on the Epidemiology of Disasters [CRED] & United Nations International Strategy for Disaster Reduction [UNISDR], 2016). The number of manmade disasters is expected to increase fivefold over the next fifty years (Thomas & Kopczak, 2005). Accordingly, there has been an increase in the number of international relief organizations to cover the demand of the communities in need. According to Muggy (2015), the number of registered US non-profit organizations grew to more than 1.5 million in 2012, up from 1,200 in 1940. With such a rapid increase in natural and manmade disasters, relief organizations will face significant challenges in coping with community needs around the globe.

When a disaster hits, NGOs, working with local organizations, quickly get involved by providing manpower and resources to help the affected communities respond to and recover from the event. According to Jobe (2011), about 10,000 NGOs were working in Haiti during the relief effort for the damage caused by the earthquake on January 12, 2010.

It is well known that humanitarian relief organizations cannot function without volunteers. According to Shin and Kleiner (2003), about 109.4 million individuals participated in volunteer work, contributing 19.9 billion hours annually with a time value of approximately $225 billion. The American Red Cross (ARC) – which responds to 7000 disasters annually – has a workforce composed of 90% volunteers (American Red Cross, 2009). Habitat for Humanity (HFH) relies heavily on volunteers to help construct or repair damaged homes. According to its annual report in 2013, HFH reached a total of one million volunteers having helped to build homes over the years. Meals on Wheels relies on its volunteers to serve more than 2.4 million seniors each year (Meals on Wheels, n.d.). These significant contributions to helping communities in need around the globe would not be achievable without the presence of volunteers.

Although millions of people volunteer with relief organizations during disaster relief efforts each year, there is a significant issue with volunteer turnover. About 33% of volunteers who volunteer one year decide not to volunteer the following year (Corporation for National and Community Service, 2007), and Jones and Berry (2017) state that many volunteer-based emergency service organizations experience volunteer turnover rates of up to 20% each year. To alleviate this problem, we must first understand the factors that cause volunteer turnover or non-retention.

Volunteers' intentions to stay with or quit the organizations they work with have been shown to be strong predictors for actual turnover (Guzley, 2002; Kosi, Sulemana, Boateng, & Mensah, 2015; Millette & Gagné, 2008). These predictors could be affected by different work environment factors such as job-fit (match/mismatch of task assignments), training, workload, volunteer groups, and supervisors. Understanding the influence of these factors on volunteer intentions is a key step toward improving volunteer retention.

Managing volunteers during relief response and recovery is challenging for a number of reasons. First, the uncertain nature of disaster outcomes makes it difficult to establish a correct estimate of a community's needs. Second, each volunteer's limited time availability and other factors cause uncertainty in the number of volunteers arriving in the affected area. For these reasons, disaster volunteers may receive mismatched task assignments or an unreasonable workload. Volunteers may also experience group conflict within the team they are working with. All these reasons may negatively impact their satisfaction and turnover intentions and may lead them to quit or to decide not to volunteer in the future. Therefore, making effective decisions when managing volunteers during disaster relief and recovery efforts not only improves efficiency in serving community needs, but also has a positive impact on volunteer satisfaction and intentions, and improves future retention rates.

The focus of this dissertation is on developing quantitative models to help decision makers at NGOs better manage their volunteers during relief efforts in order to improve retention rates. The contributions of this dissertation are to:

1. Identify volunteer and training assignments (via a mixed integer programming model) that improve how NGOs handle a range of short- and long-term community needs.

2. Investigate the effects of several work environment factors on disaster volunteers' satisfaction levels and turnover intentions.
3. Understand the effect of NGO management decision making policies on volunteer behavior and unmet community needs (via a tailored agent-based simulation model).

This dissertation includes three further chapters: Chapters 2, 3, and 4 present the completed studies. Chapter 2 presents a mixed-integer programming model for disaster volunteer assignment and training. This model aims to minimize the total costs of unmet community needs, volunteer attrition due to mismatched assignments, and volunteer expenses. Chapter 3 studies the effects of job-fit, training, workload, volunteer group, supervisor, age, gender, education, and experience on the satisfaction levels and turnover intentions of disaster volunteers. Chapter 4 proposes an agent-based modeling (ABM) approach that considers disaster volunteer satisfaction and turnover intentions in relation to management decisions during a relief event. Each chapter consists of its own introduction and related literature review, followed by explanation of the methodology and results, then a discussion of the findings and a conclusion.

CHAPTER TWO

IMPROVING VOLUNTEER PRODUCTIVITY AND RETENTION DURING HUMANITARIAN RELIEF EFFORTS

Introduction and Background

Disasters are generally classified into two types, namely natural disasters such as floods, earthquakes, or hurricanes, and manmade disasters such as hazardous materials spills, terrorist activities, and wars. Both types of disasters can cause a significant degree of damage when they occur. According to Van Wassenhove (2006), on average, 500 large-scale disasters, natural and manmade, kill about 75,000 people and affect a population of 200 million every year. Humanitarian organizations have to respond quickly by preparing and managing relief activities. A key resource for each organization is its volunteer base, and one important aspect of successful volunteer management is giving volunteers appropriate assignments, according to their desired tasks or skill levels, so that they can best help the affected population. According to Falasca, Zobel & Fetter (2009), in order to successfully retain their volunteers, humanitarian organizations should manage them appropriately and efficiently. Due to limited resources and highly variable demands in affected areas, the number of volunteers assigned to a certain task may be too low or too high in any given time period. Humanitarian organizations may thus need to train volunteers in order to reassign them to different tasks, which can pose further problems due to variable task demands for subsequent time periods.

In this chapter, a volunteer management model (VMM) is proposed to help relief managers deal with assigning and training volunteers in order to satisfy humanitarian needs, with the goal of minimizing the total expected costs of assigning volunteers, leaving needs unsatisfied, and incurring volunteer task mismatches (e.g., assigning a volunteer who is a trained nurse to a search-and-rescue team). This is one of the first models developed for assigning, training, and transferring volunteers to accomplish different tasks over a time horizon. To the best of our knowledge, no other models have been developed that specifically include volunteer training capabilities.

The organization of this chapter is as follows. We briefly introduce relevant literature in the field of humanitarian logistics, both in a general context and work that specifically addresses volunteer management. In Section 2, we introduce our VMM model, while Sections 3 and 4 contain findings generated from the modeling approach. In Section 5, we consider a special case in which all work must be completed by a specified deadline. Finally, conclusions and future work are discussed in Section 6.

While quantitative research that addresses volunteers in the field is quite limited, there are many other application areas where researchers have contributed to humanitarian crisis management during the response and recovery phases. We mention a few of these areas in particular, and then turn the focus specifically to volunteer management.

Other Humanitarian Crisis Management Areas

Evacuation is considered a challenging issue in humanitarian relief operations. Moving people from affected areas to a safe place, giving the uncertainty in the weather or the infrastructure situation, is not an easy action to be accomplished. Optimization models have been developed to handle some of these evacuation issues. For instance, Cova & Johnson (2003) introduced a network flow model to identify optimal lane-based evacuation routing plans in a complex road network. They used a mixed integer programming approach to find optimal evacuation routing plans for a sample network. In another study, Yi & Özdamar (2007) proposed a mixed integer multi-commodity network flow model for evacuation and support in disaster response activities. An earthquake scenario based on Istanbul's risk grid, as well as larger size hypothetical disaster scenarios, were used to illustrate the model. In addition, there are many studies considering evacuation planning for disasters, (Duanmu, Taaffe & Chowdhury, 2010; Jha, Moore & Pashaie, 2004; Pidd, De Silva & Eglese, 1996; Simonovic & Ahmad, 2005; Tovia, 2007).

When evacuation is not an option and residents must shelter-in-place, we turn our attention to providing aid to the disaster-stricken area. *Last mile distribution* refers to the delivery of relief supplies from distribution centers to people in the affected areas. Many studies have focused on this area. Barbarosogu & Arda (2004) developed a scenario-based stochastic programming model to represent a multi-commodity, multi-modal network flow problem. The main goal was to minimize the loss of life and maximize the efficiency of search and rescue operations. Balcik, Beamon, & Smilowitz (2008) proposed a mixed integer programming model to optimize resource allocation and routing decisions from a number of local distribution centers to a number of demand locations, with the goal of minimizing the transportation costs and maximizing the recipients' benefits, keeping into account vehicle capacity and delivery time restrictions. The best allocation can be easily found, however, only for problems with small numbers of nodes and routes. Hentenryck, Bent & Coffrin (2010) proposed a multi-stage stochastic hybrid optimization algorithm for the single commodity allocation problem (SCAP) for disaster recovery. The objective was to minimize the amount of unsatisfied demands, the time it took to satisfy the demand, and the storing costs of the commodity. To validate the algorithm, it was used in hurricane disaster scenarios generated by Los Alamos National Laboratory. For more examples in literature (Haghani & Oh, 1996; Knott, 1987)

The inventory management in humanitarian logistics has received some attention from the optimization modeling perspective. Beamon & Kotleba (2006) developed a stochastic inventory control model that determines optimal order quantities and reorder points for a long-term emergency relief response. In another study, Ozbay & Ozguven (2007) developed a stochastic inventory control model for disaster planning. The goal was to determine the optimal amount of initial stock to prevent disruption during the delivery and consumption process. In a third study, Blecken, Danne, Dangelmaier, Rottkemper & Hellingrath (2010, January) formulated an inventory relocation model that relocated the optimal stock under demand uncertainty in risk-prone post-disaster scenarios. It was shown that the overall inventory cost could be significantly reduced when considering demand uncertainty in post-disaster scenarios. As policies are created to support humanitarian relief distribution, we require resources in the field to provide delivery, support, and other functions. In other words, we cannot look at these important issues without considering how the role of the volunteer worker impacts humanitarian aid policies.

Volunteer Management

In volunteer management and scheduling, not much work has been done compared to traditional labor management. In one study, Gordon & Erkut (2004) developed a spreadsheet-based decision support tool to generate shift times and schedule volunteers for the Edmonton folk music festival. They used integer programing formulation to handle the task preferences, with the goal of minimizing the number of surplus volunteers. In contrast, the cost of volunteer shortages was not clearly considered. Sampson (2006) demonstrated how volunteer labor assignment (VLA) problems are quite different from traditional labor assignment (TLA) problems. He considered the volunteer as a laborer with no cost; then he incorporated this difference into a goal programming model. In VLA, the goal was to minimize the total cost of assigning too few or too many volunteers, volunteer assignments, and unsatisfied task demand. Falasca, Zobel & Fetter (2009) developed a multi-criteria optimization model to help in assigning volunteers to tasks. As with Sampson (2006), they reviewed the differences between a volunteer labor assignment and a traditional labor assignment. In another study, Falasca, Zobel & Ragsdale (2011) discussed the creation of a spreadsheet multi-criteria volunteer scheduling model for helping a small development organization in a developing south American country. The goal of the model was to reduce the number of unfilled shifts, minimize the total scheduling costs, and minimize undesired assignments. This study is different from Sampson (2006) in that it considers that the volunteer labor cost is not negligible, such as travel expenses.

What research has been done in volunteer management assignment motivates us to explore more in this area. This topic has been lightly studied to date, yet it is one of the key components to any relief organization's efforts. In the model described below, we expand on the topics covered by similar models such as VLA, but also explore new ideas, such as volunteer training for different tasks and volunteer attrition due to volunteer task assignment mismatching.

Humanitarian Volunteer Management Model

This model is designed to help humanitarian organization managers effectively and efficiently manage volunteer resources in the aftermath of a disaster. The consequences of poor volunteer resource allocation can directly affect the ability of the organization to meet the short-term and long-term needs of the community. For example, little elaboration is necessary to imagine the impacts of not having enough skilled volunteers available for a search-and-rescue effort immediately following an earthquake. However, assigning too many volunteers to certain tasks at the expense of other tasks can also cause serious problems in the long term as well. For example, if too few volunteers are assigned to preventative cholera outbreak measures due to seemingly more pressing immediate tasks, then a cholera epidemic could break out that perhaps was avoidable. This model serves to help prevent these types of issues from occurring, via a mathematical approach to volunteer resource management.

The objective is to minimize the total expected cost of volunteer transportation/living expenses, unmet task demand costs (in terms of time delays, relief aid shortages, etc.), and volunteer retention costs (the costs of losing volunteer(s) due to mismatched volunteer assignment preferences). The latter cost seeks to identify the impact of unnecessarily assigning volunteers to tasks for which they did not request, (e.g., an electrician working in triage or an unskilled volunteer working as a carpenter). In particular, we want to measure the negative impact on volunteer goodwill and the likelihood of their remaining on-site during the crisis. Initial data that is required by the model includes periodic task demands (deterministic or stochastic), available resource pool and their skill levels, and the costs associated with volunteer training, unmet task demand, etc. Overall, the constraints (1) limit the number of available volunteers within each group, (2) account for period(s) when volunteers being trained are able to assist in their new task at a limited efficiency as they undergo on-the-job training, and (3) account for changing future task demands based on current task progress by the volunteers.

A key component of this model is its ability to incorporate a variety of task demand scenarios to represent changing short-term and long-term community needs. It is logical to assume that task demand for a crisis response would not be known with certainty. In an attempt to factor in uncertain task demands, multiple task demand scenarios with respective probabilities can be introduced into the model, which in turn allows the model to best place volunteers based on the expected task demands for each period. Next, we provide the details of the model formulation, including all decision variables and parameters specified within the formulation.

Decision Variables

$v_{ijt\alpha}$: Volunteers with skill i, assigned to task requiring skill j, for time period t, with α training periods remaining

V_{it} : "Pool" of volunteers with skill i in period t

w_{jst} : Volunteer hours for task requiring skill j, under scenario s, for time period t

$\hat{d}_{jst}$: Additional task demand (time units) caused by previous unfulfilled task demands, for task requiring skill j, under scenario s, for time period t

Note that the model will provide the optimal volunteer assignments $v_{ijt\alpha}$ based on all possible task demand scenarios and their respective probabilities (or likelihood of occurrence). Only one course of action can actually be chosen, thus $v_{ijt\alpha}$ is not specified for each demand scenario. The initial volunteer set for all skill levels (V_{i1}) are defined. The following is a list of the other parameters under consideration for the volunteer management model.

Parameters

$\bar{d}_{jst}$: Task demand (time units) requiring volunteers with skill *j*, under scenario *s*, for period *t*

K_j : Penalty factor for unmet volunteer task (with skill *j*) demand, $K_j \geq 1$

z_j : Time required to train a volunteer for skill *j* (in periods)

e_j : Volunteer efficiency factor for assignment with skill *j* (mismatched volunteers only)

h_j : Volunteer work-hours multiplier per assignment *j*

P_s : Probability that demand scenario *s* will occur

A_{ij} : Assignment preference mismatch factor for volunteer with skill *i* assigned to task requiring skill *j* (in terms of # of volunteers)

$C^A{}_i$: Volunteer with skill *i* attrition cost

$C^{E}{}_{j}$: Unmet volunteer task requiring skill *j* demand cost, final period only

$C^{M}{}_{i}$: Per-period volunteer with skill *i* assignment mismatch cost

$C^{U}{}_{j}$: Per-period cost of unmet volunteer task (with skill *j*) demand

$C^{V}{}_{i}$: Per-period volunteer with skill *i* costs (transportation, living, others)

I : Number of different skill/task levels

S : Number of total task demand scenarios

T : Number of periods

Formulation

To summarize, our desire is to minimize total expected assignment cost of volunteer resources to task demands per period. Using a formulation based on the likelihood of various task demand scenarios occurring, along with the decision variables and parameters previously introduced, we can now present the formulation of the Volunteer Management Model (VMM).

$$\textbf{MIN}\left(\left(\sum_{j=1}^{I}\sum_{s=1}^{S}\sum_{t=1}^{T-1}\boldsymbol{P_s}\times\boldsymbol{C_j^U}\times\boldsymbol{\hat{d}_{jst}}\right)+\left(\sum_{j=1}^{I}\sum_{s=1}^{S}\boldsymbol{P_s}\times\boldsymbol{C_j^E}\times\boldsymbol{\hat{d}_{jsT}}\right)+\left(\sum_{i=1}^{I}\boldsymbol{C_i^V}\sum_{j=1}^{I}\sum_{t=1}^{T}\sum_{\alpha=0}^{z_j}\boldsymbol{v_{ijt\alpha}}\right)\right.$$
$$+\left(\sum_{i=1}^{I}\boldsymbol{C_i^A}(\boldsymbol{V_{i1}}-\boldsymbol{V_{iT}})\right) \tag{2-1}$$
$$\left.+\sum_{i=1}^{I}\boldsymbol{C_i^M}\sum_{j\neq i}\sum_{t=1}^{T}\sum_{\alpha=0}^{z_j}\boldsymbol{v_{ijt\alpha}}\right)$$

<u>Subject to</u>

$$\boldsymbol{\hat{d}_{jst}} = \left(\boldsymbol{\bar{d}_{jst}}+\boldsymbol{\hat{d}_{js(t-1)}}-\boldsymbol{w_{jst}}\right)\boldsymbol{K_j} \quad \forall\, \boldsymbol{j}, \boldsymbol{s}, \boldsymbol{0} < t \tag{2.2}$$

$$\boldsymbol{w_{jst}} \leq \left[\sum_{i\geq j}\boldsymbol{v_{ijt0}}+\left(\sum_{i<j}\sum_{\alpha>0}\boldsymbol{v_{ijt\alpha}}\right)\boldsymbol{e_j}\right]\boldsymbol{h_j} \quad \forall\, \boldsymbol{j}, \boldsymbol{s}, \boldsymbol{t} > 0 \tag{2.3}$$

$$\boldsymbol{V_{it}} \leq \boldsymbol{V_{i(t-1)}} - \sum_{j>i,\alpha>1} \boldsymbol{A_{ij} v_{ij(t-1)\alpha}} - \sum_{j<i} \boldsymbol{A_{ij} v_{ij(t-1)0}} - \sum_{j>i} \boldsymbol{v_{ij(t-1)1}} + \sum_{m<i} (\boldsymbol{1} - \boldsymbol{A_{mi}}) \boldsymbol{v_{mi(t-1)1}} + \boldsymbol{0.5} \quad \forall \boldsymbol{i}, \boldsymbol{t} > 1 \tag{2.4}$$

$$\boldsymbol{v_{ijt(\alpha-1)}} \leq \boldsymbol{v_{ij(t-1)\alpha}} \left(\boldsymbol{1} - \boldsymbol{A_{ij}}\right) + \boldsymbol{0.5} \quad \forall \boldsymbol{i} < j, t > 1, \alpha \geq 1 \tag{2.4}$$

$$\sum_{j=1}^{I} \sum_{\alpha=0}^{z_j} \boldsymbol{v_{ijt\alpha}} \leq \boldsymbol{V_{it}} \quad \forall\, \boldsymbol{i}, \boldsymbol{t} > 0 \tag{2.6}$$

$$\widehat{\boldsymbol{d}}_{jst} = \boldsymbol{0} \quad \forall \boldsymbol{j}, \boldsymbol{s}, \boldsymbol{t} = \boldsymbol{0} \tag{2.7}$$

$$\boldsymbol{v_{ijt\alpha}} = \boldsymbol{0} \quad \forall \boldsymbol{i} \geq \boldsymbol{j}, \boldsymbol{\alpha} \neq \boldsymbol{0}, \boldsymbol{t} > 0 \tag{2.8}$$

$$\boldsymbol{v_{ijt\alpha}} = \boldsymbol{0} \quad \forall \boldsymbol{i} < j, 0 < t \leq \boldsymbol{z_j}, \boldsymbol{\alpha} \leq \left(\boldsymbol{z_j} - \boldsymbol{t}\right) \tag{2.9}$$

$$\boldsymbol{v_{ijt\alpha}} = \boldsymbol{0} \quad \forall \boldsymbol{i} < j, t > 0, \boldsymbol{\alpha} > \boldsymbol{z_j} \tag{2.10}$$

$$\boldsymbol{v_{ijt\alpha}}, \boldsymbol{V_{it}}, \boldsymbol{w_{jst}}, \widehat{\boldsymbol{d}}_{jst} \geq \boldsymbol{0} \quad \forall\, \boldsymbol{i}, \boldsymbol{j}, \boldsymbol{s}, \boldsymbol{t}, \boldsymbol{\alpha} \tag{2.11}$$

$$\boldsymbol{v_{ijt\alpha}}, \boldsymbol{V_{it}} \quad \boldsymbol{integer} \quad \forall\, \boldsymbol{i}, \boldsymbol{j}, \boldsymbol{t}, \boldsymbol{\alpha} \tag{2.11}$$

Constraint Explanations

The objective function serves to minimize costs to the relief organization, measured in terms of the expected cost of unmet task demand, the expected cost of not completing the total volunteer task demand by the final time period, cost per volunteer per time period (for travel, living expenses, etc.), cost for volunteer attrition (lost volunteers from assignable causes), and the cost of mismatching volunteer tasks with their respective skill levels. If the cost of leaving task demand unmet is not significant, then C^E can be set equal to C^U, thus leaving C^U as the sole cost driver. It is logical that

$C^E \geq C^U$ for all tasks j. Constraint (2-2) defines the amount of additional task demand ($\hat{d}$) created per time period, based on the difference between task demands (or needs) and the actual work accomplished. This difference is then multiplied by a penalty factor K_j, implying that the unmet task demands may increase needs in future periods.

Constraint (2-3) confines the volunteer work completed on a task in a certain period to be no more than what can be done by the assigned volunteers that are already trained for the task, plus the untrained volunteers currently going through training for that task. Volunteers initially assigned to a task for which they were not already skilled go through a training period of length z_j, during which they are only a factor amount e_j as efficient before they are fully trained. The number of periods left in training is tracked by the index α. Notice the volunteer hours multiplier h_j.

Constraint (2-4) defines the number of available volunteers in the next time period for each skill level i to be equal to the current number of available volunteers in skill level i. The constraint also accounts for the number of volunteers who leave due to the mismatching of assignments and preferences or who are moving from one skill level to another skill level upon the completion of training. The constant 0.5 is included to cause the volunteers available to round to the nearest integer, without losing linearity in the model via rounding or truncating functions. Constraint (2-5) tracks the progress of the volunteers in training, by updating their remaining training periods value α. Volunteers lost due to assignment preference mismatches are accounted for as well. The constant 0.5 is included to cause rounding to the nearest integer, as in constraint (2-4). Constraint (2-

6) limits the number of assigned volunteers to be less than or equal to the number of available volunteers at the beginning of the period, for each skill level.

Constraints (2-7), (2-8), (2-9), and (2-10) prohibit invalid decision variables. Constraint (2-8) prohibits additional task demand prior to the model's first time period, period 0 (necessary due to subscript definitions). Constraints (2-8), (2-9), and (2-10) prohibits invalid volunteer assignment variables, i.e. v_{1210} (if some training is required of a volunteer of skill level one assigned to a task requiring skill level two, thus the training periods remaining must be greater than zero in the first period). Constraints (2-11) and (2-12) satisfy non-negativity and integer constraints for the decision variables.

Please note that skill levels are numerically hierarchical. That is, volunteers of skill level one are less skilled than volunteers of skill level two, two are less than three, and so on. Thus, training only occurs for volunteer assignments to tasks above their skill level.

Model Behavior and Volunteer Assignments – An Example

Base Conditions and Methodology

As stated earlier, a key component of this model analyzed is the task demand variability component, represented through each task demand scenario *s*. Variability in the amount of relief needed is endemic to humanitarian crisis response, given the volatile and ever-changing nature of disaster situations. This is accounted for by allowing multiple different possible demand scenarios, and respective probabilities, to be inputted into the model, which then subsequently generates volunteer assignments based on the lowest expected cost. For the sake of analysis, it is assumed that the parameters C^{V}_{i} (per-

period volunteer costs), $C^A{}_i$ (volunteer attrition cost), and $C^M{}_i$ (per-period volunteer assignment mismatch cost) are constant, as these values can be estimated by the relief organization.

The following example is modeled off a potentially real humanitarian disaster situation. After a disaster, there are immediate short-term task demands (food, water, shelter) as well as long-term recovery task demands (primarily reconstruction). For this example, two task demands are considered, broadly characterized as short term (task/skill type 1) and long term (task/skill type 2). These require unskilled and skilled volunteers respectively, since long-term needs generally involve tasks such as reconstruction of homes and infrastructure. Unskilled volunteers can still be assigned to long-term recovery tasks, but at a lower efficiency as previously described. Four potential task demand scenarios are considered due to the uncertain task demands that may be encountered by a humanitarian relief organization; they are displayed in Figures 2.1-2.4. There are 100 volunteers in each skill level, and the collective volunteer pool can satisfy a maximum of 7000 units of demand and 5600 units of demand for unskilled and skilled tasks, respectively. For each task demand scenario, the general idea is high short-term response needs initially, with varying patterns for long-term recovery needs. The peaks of each task demands are purposefully higher than the stated maximums in order to encourage variable volunteer assignments over time.

Scenario 1 is designed to represent a “classic” two-phase response, with high initial short-term task demands that gradually decrease over time, and long-term task demands that are initially low but gradually increase to a peak around the middle of the predetermined response window. As seen in Figure 2.1, the short-term tasks are modeled to exponentially decrease from an initial peak value, while long-term tasks generally follow a normal distribution. Scenario 2 has steadily decreasing short-term task demands, and constant long-term task demands that are approximately half of the initial short-term task demands. Scenario 3 has high short-term task demands that only begin to decrease after the 6th week, while the long-term task demands constantly increase to week 12, then decrease beginning in week 17. This could represent a crisis in which there are high immediate needs, but then some unforeseen circumstance causes a rise in long-term recovery needs weeks or months later. Scenario 4 has steady, high short-term task demands through week 6 after which they exponentially decrease; the long-term task demands begin low but increase to a high constant value beginning in week 3. This latter scenario may most accurately represent an "overwhelming" humanitarian crisis, where there are so many long-term recovery needs that they can only be represented as "high" for an indefinite horizon.

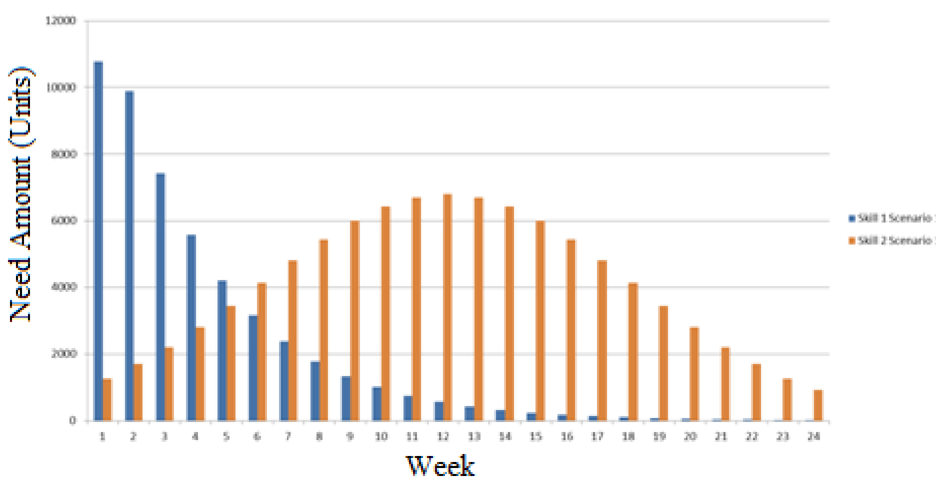


Figure 2.1 Task Demands Scenario 1

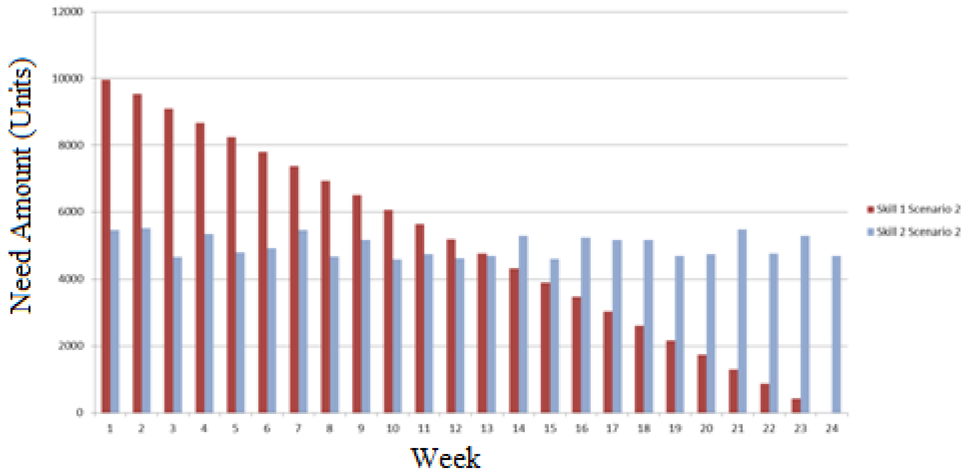


Figure 2.2 Task Demands Scenario 2

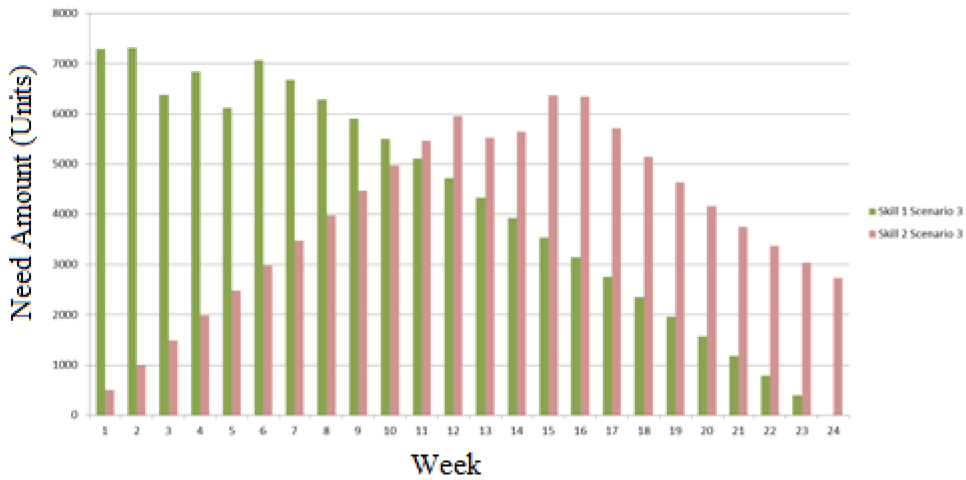


Figure 2.3 Task Demands Scenario 3

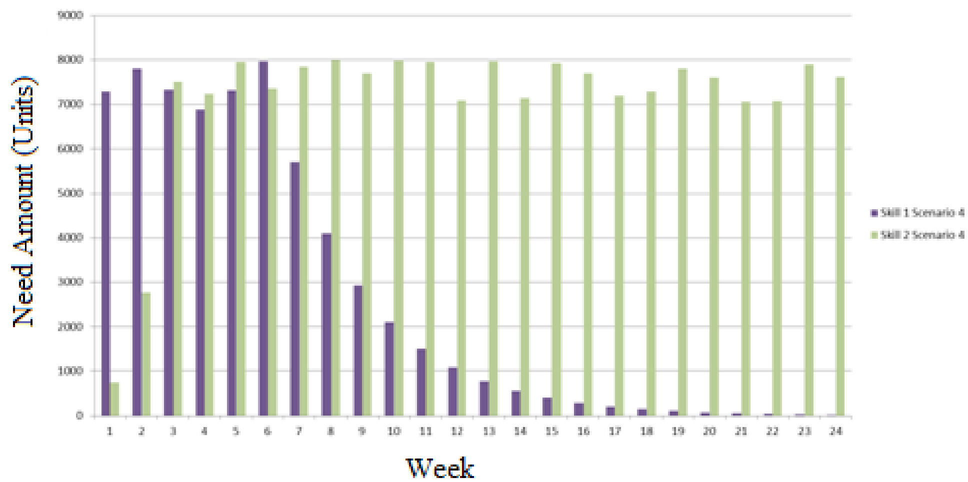


Figure 2.4 Task Demands Scenario 4

For the analysis that follows, these constants are used unless otherwise specified, and the unit time period is in weeks.

I=2, S=4, T=24

A_{12}=0.01, A_{21}=0.02

V_{11}=V_{21}=100

e_1=0.95, $e_2=0.50$

h_1=70, h_2=56

z_1 =0, z_2=6

$C^A{}_1$ =350, $C^A{}_2$ =210

$C^E{}_1$=$C^E{}_2$=10

$C^M{}_1$=3.5, $C^M{}_2$=4.2

$C^U{}_1$=$C^U{}_2$=10

$C^V{}_1$=$C^V{}_2$=350

K_1=1.5, K_2=1.1

Unskilled volunteers training and/or working in skilled (long-term recovery) tasks are assumed to satisfy task demands at only half the rate of a skilled volunteer. Short-term recovery tasks volunteers are assigned to work 70 hours/week (10 hours/day) due to the urgent nature of immediate tasks, while long-term recovery volunteers are assigned to work 56 hours/week (8 hours/day). A six week training period is defined for unskilled volunteers to become skilled. Unmet task demand costs were set at $10/hour for both task types, in the absence of realistic data. Volunteer attrition costs were set equal to the cost of the unmet task demand amount they could individually satisfy per period (C^U *h), minus the per-period volunteer costs (C^V), which are assumed to be $50/day. Volunteer mismatch costs are roughly estimated by simply taking volunteer attrition costs and multiplying it by the respective attrition probability (A_{ij}). Finally, the unmet task demand penalty factor K_j is higher for short-term recovery tasks than long-term recovery tasks, since it is assumed that short-term tasks are more urgent and thus would cause problems (in terms of additional task demands) if they are not satisfied in a timely manner.

Model Behavior and Insights

The basic decision characteristics of the VMM are first analyzed via a simple sensitivity analysis. The volunteer assignments decisions created by the model are primarily influenced by the values of the parameters related to the task demands: $C^U{}_j$ (per-period cost of unmet task demand), $C^E{}_j$ (unmet volunteer task demand cost, final period only; assumed to be related to $C^U{}_j$), and K_j (penalty factor for unmet volunteer task demand). These parameters are the primary drivers behind the calculation and impact of additional task demands ($\hat{d}$), which is a key decision variable in the model. Modifying their values reveals the fundamental model behavior.

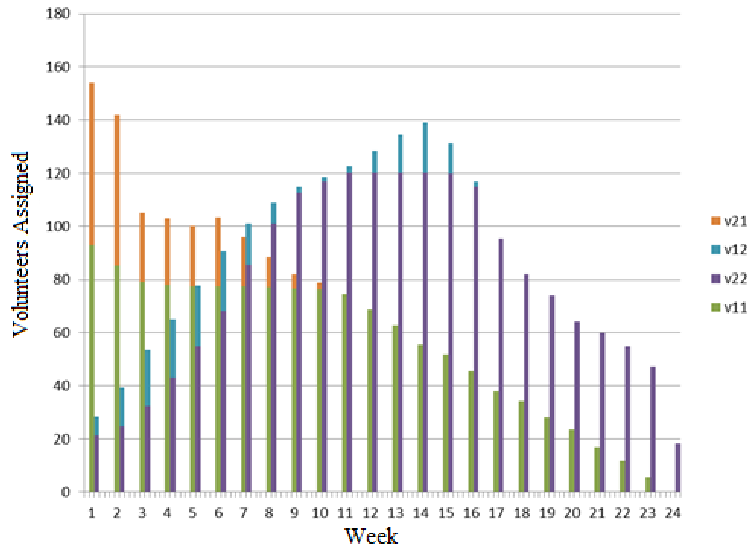
Regardless of the scenario(s) chosen, reducing the value of the unmet task demand costs ($C^U{}_j$, and corresponding $C^E{}_j$) always tended to increase the amount of unmet task demand ($\hat{d}$), when all other parameters are unchanged. This is because the VMM found it less costly to leave some or most of the task demand unmet than to assign the volunteers necessary to cover the task demand in its entirety. This is mathematically determined by the relative values of $C^V{}_i$ and $C^U{}_j$; the higher the cost is per volunteer assignment, proportionally fewer volunteers will be assigned in relation to the unmet task demands. The VMM does tend to leave some task demand unmet in the final period in most parameter configurations, due to the relative values of each and their equal weighting in the objective function. This is perhaps unrealistic in some humanitarian relief operations, and thus motivated the inclusion of the last period unmet task demand cost ($C^E{}_j$) to discourage this decision. Increasing this parameter value to be greater than the unmet task demand cost ($C^U{}_j$) tends to reduce the amount of unmet task demand at the end of the last period, if possible depending on volunteer availability.

When the penalty factor (K_j) is set to the lowest sensible value of 1.0, the unmet task demand ($\hat{d}$) is simply the cumulative sum from each period. However, as the penalty factor is increased, the amount of unmet task demand ($\hat{d}$) tended to decrease, assuming enough volunteers are available to meet the task demand and the other parameters are unchanged. This is explained by the model choosing the more cost effective option of assigning more volunteers to the relief operation, rather than the more costly option of generating excessive additional task demands by not doing so.

Another key component to this model is the training and/or assignment of volunteers to tasks which do not meet their current skill level. In a humanitarian crisis response, there will likely be times where some volunteers (i.e. carpenters) are needed to help in another field by necessity (i.e. search-and-rescue) due to personnel shortages.

An Example – Combined Scenarios 1 and 3

Humanitarian relief organizations cannot be certain of their projected task demands, and thus there may be several forecast scenarios with different probabilities of occurring. In Section 4, we will provide a more comprehensive analysis of various combinations of scenarios, with equal likelihoods of each scenario included in the combination. As an example, task demand scenarios 1 and 3 were considered to be equally likely, and Figure 2.5 provides the resulting volunteer assignments.



v21: Skilled (long-term) volunteers assigned to an unskilled (short-term) task

v12: Unskilled (short-term) volunteers assigned to a skilled (long-term) task

v22: Skilled (long-term) volunteers assigned to a skilled (long-term) task

v11: Unskilled (short-term) volunteers assigned to an unskilled (short-term) task

Figure 2.5 Scenarios 1 and 3 Equally Likely

Notice that unskilled volunteers were being trained for skilled tasks at the same time that skilled volunteers were assigned to short-term recovery tasks. This “double mismatching” in theory seems illogical, as volunteers should usually be assigned to the tasks appropriate for their skill level, and only “mismatching” uni-directionally to help fill a particular volunteer need. However, the optimum decision is to begin training some unskilled volunteers early in the response period when the short-term task demands are still high, in preparation for the upcoming long-term task demand peak around the middle of the response period. Thus, additional skilled volunteers are mismatched to cover the volunteer void created by the unskilled volunteers training for the long-term tasks. This phenomenon is interesting, as it suggests a proactive approach to volunteer management by encouraging volunteer training early, in advance of the peak task demand periods. For the specific example in Figure 2.5, a skilled volunteer pool of 120 people (versus the initial 100) is ready in time for the long-term task demand peak around periods 12-16. In short, if there are sufficient numbers of volunteers to cover both short and long-term task demands initially, the VMM model proposes to preemptively train unskilled volunteers in advance of a future forecasted skilled needs increase.

Findings – Base, Training, and Mismatching Policies

To further illustrate the benefits of the VMM to assign volunteers to tasks and training based on anticipated needs scenarios, examples are shown below comparing identical humanitarian crisis situations with different volunteer assignment rules. Each task demand scenario combination is tested, with equal scenario probabilities across each scenario in the combination. For each combination, the base case is analyzed (where volunteer training and mismatching is allowed to occur as is standard in the VMM), as well as cases where either or neither type of volunteer assignment (training and/or mismatching) are allowed. The benefits are quantified via cost analyses, unmet demand amounts, and volunteer attrition.

Parameter values from Section 3 are adopted here, with the exception of the unmet task demand penalty factor (K_j). Preliminary testing with this data set and K_j ranging from 1.1 to 1.5 led to extreme amounts of additional demands being generated due to a lack of available volunteers. This is qualitatively useful, as it can help relief managers gain insight into situations where relief needs could grow out of control. This type of "runaway" scenario instance could be roughly compared to a disease outbreak, where if a small disease problem is not able to be treated effectively by the volunteer staff, then a much larger disease outbreak could occur later. The fact that even a marginal increase in these parameters appears to have such a dramatic effect in subsequent periods is noteworthy. However, for the sake of obtaining quantitative results for comparison between the different volunteer assignment rules, no additional task demand will be generated after each period (i.e., K_j=1.0), but unmet task demand from the previous period will still be carried over to the next period.

For the purpose of these examples, 10 sets of task demands per scenario are generated, where the demands per period vary up to +/- 10% of the values given in the scenarios shown in Section 3. The model is run 10 times (once per data set), and these results are then averaged together for each volunteer assignment restriction (Base, No Training, No Mismatching, and Neither). It was observed during testing that greatly differing solutions to the VMM could occur between each data set, due to the predesigned tight numbers of idle volunteers during peak needs periods. Thus, an average is necessary to capture the possible diverse model results.

One general trend noticed throughout many of the examples again was the tendency for the remaining task demands in the last scenario to only be partially met, often for the skilled/long-term tasks. This is explained by the values of the volunteer assignment cost (C^V) and the last period unmet task demand cost (C^E) chosen for this series of examples; modifying the relationship between these cost parameters could affect this tendency noticeably, as discussed in Section 3.2. The full numeric results of the testing ((% of Base) are shown in Table 2.1, accompanied graphically in Figure 2.6.

Table 2.1 Training/Mismatching Averaged Performance Results

Case	Total expected Cost	Volunteer Costs	Cost of Unmet Task Demand	Volunteers Lost	Change in Unskilled Pool	Change in Skilled Pool
Base	100%	100.0%	100%	0.91	-30.0	28.4
No Training	137%	88.7%	2724%	0.06	0.0	-0.1
No Mismatching	112%	99.8%	1114%	0.50	-27.2	26.7
Neither	146%	90.4%	3547%	0.00	0.0	0.0

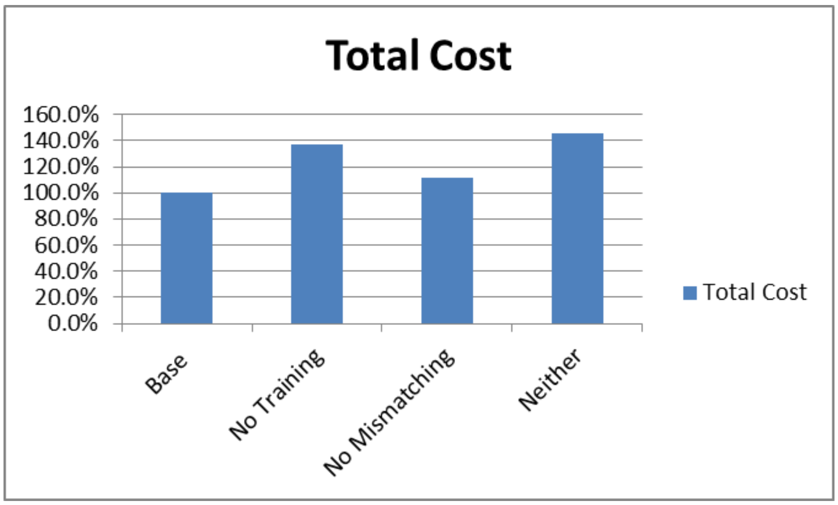


Figure 2.6 Total expected Costs Across Training/Mismatching Cases

In summary, allowing for volunteer training and mismatching (as in the base formulation of the VMM) results in the lowest total expected cost for all examples. Although the total expected costs vary widely between examples due to the different needs' distributions, the important point is that the lowest expected cost for each example always occurred in the base case. The model has the flexibility to shift volunteers from need to need to cover as much task demand as possible. On the other end of the spectrum, preventing any volunteer training or mismatching from occurring (i.e., not allowing any shifting) always resulted in the highest expected cost as the organization could not make changes to address the particular needs situation.

Comparing the “no training” and “no mismatching” restrictions is more complicated. For all examples, the total expected costs for both cases lie between the base case and the “neither” case. Thus, the prudent comparison was to look at the relative costs for each type of single restriction. The “no training” cases had higher total expected costs relative to their “no mismatching” cases in the following scenario combinations:

1, 4, 1&3, 1&4, 2&4, 3&4, 1&2&4, 2&3&4, 1&2&3&4

While the “no mismatching” cases had higher total expected costs in scenario combinations:

2, 3, 1&2, 1&2&3, 2&3

Studying the task demands scenario graphs (Figures 2.1-2.4), it is clear that the sustained high needs for skilled volunteers in scenario 4 is significant. In those examples, their base case had substantial amounts of volunteers trained by the VMM in order to cover the skilled/long-term task demands. Restricting training causes much higher unmet task demand costs and thus total expected cost. Due to the presence of attrition parameters (A_p), training large numbers of volunteers does result in some volunteer attrition and corresponding volunteer attrition costs (C^A), but they are outweighed by the unmet task demand costs that newly trained volunteers help to prevent. However, this does mean that these examples with “no training” do have lower volunteer attrition. In short, humanitarian relief organization managers who generally feel as though a peak of long-term/skilled volunteer task demands will come at some point during the disaster response should strongly consider allowing volunteer training assignments.

Another way of representing the benefits of allowing volunteer training in a humanitarian relief response is shown in Table 2.2 below. This table computes the ratio of the total expected cost difference and training cost difference between the examples' base cases and "no training" cases. This quantifies the total cost savings per dollar spent on volunteer training costs. In most cases, the VMM suggests that the training investment is well worth it, given the parameters used in this series of tests.

Table 2.2 Training Value

Case	Value (Total cost reduction) per $1 training investment
Scenario 1	$1121.81
Scenario 2	$31.47
Scenario 3	$133.04
Scenario 4	$1958.09
Scenarios 1 & 2	$3.83
Scenarios 1 & 3	$545.02
Scenarios 1 & 4	$1166.97
Scenarios 2 & 3	$73.33
Scenarios 2 & 4	$483.66
Scenarios 3 & 4	$643.66
Scenarios 1 & 2 & 3	$225.84
Scenarios 1 & 2 & 4	$521.44
Scenarios 2 & 3 & 4	$282.25
Scenarios 1 & 2 & 3 & 4	$354.65

Conclusions and Future Work

The formulation of the Volunteer Management Model (VMM) was presented. The objective function and constraints were explained, along with the assumptions made by the model. A series of practical examples with short and long-term task demands was presented. The various features displayed by the model were discussed in the corresponding sensitivity analysis; complex parameter interactions on the objective function were observed, as well as preemptive training assignments in certain task demand scenarios. Much more analysis will be necessary to understand the true nature of these interactions. Possible additions to the model were described as well, some of which may be incorporated in future versions of the VMM pending discussions with interested parties.

This model is a good start to determining volunteer assignments for a humanitarian organization responding to a crisis. Several useful features are included, such as volunteer skill levels and training, scenario-based costing, and additional task demand generated by unmet task demand from prior periods. However, several assumptions are made as well which limit the capability of the model to a degree, such as not tracking volunteers with partial training completions or assuming that all of the requested cost parameters are known with relative accuracy. Placing these aside, the VMM has plenty of useful insight yet to be analyzed and is currently capable enough for field testing.

Currently, the model only accounts for volunteers lost due to assignment preference mismatches, where there may be many other reasons that may make volunteers think about quitting the organization (e.g., workload, volunteer group, and supervisor) which will be the focus of chapter 3. The model also does not have a parameter to control scheduled volunteer arrivals and departures, or a penalty cost for idle volunteers, which sometimes is a more common problem for humanitarian relief organizations than volunteer shortages. It would be interesting to consider the ability to reassign tasks/demands to other organizations, along with any costs of doing so. This could prevent any unmet demands from multiplying and overwhelming the original humanitarian organization. As discussed earlier, a practical example of this would be disease control and prevention, where falling behind on preventive health measures could be very costly later.

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CHAPTER 3

INVESTIGATING THE INFLUENCE OF WORK ENVIRONMENT FACTORS ON TURNOVER INTENTIONS OF DISASTER VOLUNTEERS

Introduction

There are a range of possible predictors for volunteer turnover and retention. Among the most direct antecedents to these phenomena are the intention to quit or to stay (Kosi, Sulemana, Boateng, & Mensah, 2015; Millette & Gagné, 2008; Queiri, Yusoff, & Dwaikat, 2015). Level of satisfaction also may predict turnover and retention, directly or indirectly. According to Galindo-Kuhn and Guzley (2002), level of satisfaction is a measure that may enhance an individual's intention to stay with or quit an organization, which in turn contributes to predicting turnover and retention. Understanding the antecedents of actual behaviors is a vital step toward improving actual behaviors. In Chapter 2, volunteer turnover was represented as a percentage of mismatched volunteer assignments. In this chapter we intend to investigate the impact of work environment factors on volunteer satisfaction and turnover intentions.

There is a plethora of literature on investigating the influence of different work environment factors on the satisfaction and turnover intentions of employees and volunteers from different contexts (Proença, 2012; Elstad, 2003; Hustinx, 2010; Bang, Won & Kim, 2009; Coomber, & Barriball, 2007; Lambert, Hogan& Barton, 2001; Lee, 1995). Such previous studies have concentrated on a range of work environment factors such as training, job-fit, workload, and interpersonal relationships, which are also the focus of our study. However, research specifically considering the *satisfaction and* *turnover intentions of disaster volunteers* is sparse (Steerman & Cole, 2009). Therefore, the purpose of this study is to analyze the effects of selected work environment factors on these under-explored predictive factors. Structural equation modeling is used to test whether workload, supervisors, training, volunteer group relations, and job-fit can explain the variability of the satisfaction levels and turnover intentions of disaster volunteers.

In the rest of this chapter, we will review the related literature and then establish the relevant measures for our study; state our hypotheses, explain our methodological approach, and introduce the instrument; analyze and discuss the findings; summarize our conclusions; and recommend future work.

Literature review

In the next few sections, a literature review is provided for turnover intentions, satisfaction, work environment factors, and volunteer characteristics.

Intention to stay and intention to quit

The intention to quit is defined as a mental consideration of an individual to leave the current employer for the next year (Gill, Mathur, Sharma & Bhutani, 2011). For this study, the intention to quit would be defined as the desire of a volunteer to stop participating in disasters with the current organization, within a certain amount of time. It is a reliable indicator that volunteers will likely leave their organizations (Millette & Gagné, 2008).

Inversely, the intention to stay is defined as the degree to which employees plan to stay with their organization (Price, 2001). For this study, the intention to stay would be defined as the likelihood to continue volunteering in disasters with the current organization for a certain amount of time. The intention to stay is a reliable predictor that reflects how likely a volunteer is to stay with the organization. Intention to stay negatively correlates with turnover (Kosi, Sulemana, Boateng, & Mensah, 2015; Queiri, Yusoff, & Dwaikat, 2015).

Due to their direct impact on actual behaviors, the intention to stay or quit have had considerable attention in the literature in different volunteering fields, such as social work, sports, healthcare, emergency, and tourism.

Satisfaction

Satisfaction has been considered an essential antecedent to turnover intentions and actual behaviors (Ellenbecker, 2004; Steijn, 2005; Vecina, Chacón, Sueiro, & Barrón, 2012). For example, Ellenbecker (2004) studied the factors that affect the intention to stay and retention for home healthcare nurses and found that job satisfaction was directly related. In addition, Steijn (2005) concluded that employees who show dissatisfaction with their organizations are more likely to look for opportunities in other organizations. Vecina, Chacón, Sueiro, & Barrón (2012) studied the relationship between work engagement, satisfaction, and intention to stay for volunteers from different nonprofit organizations and found that volunteer satisfaction is the main factor to explain the intention to stay with a certain organization.

Work environment factors

Turnover intentions, actual behavior, and satisfaction are influenced by several work environment factors, such as training, job fit, workload, group work, relationship with peers, and relationship with the supervisor. Although volunteer satisfaction, intention to stay, and intention to quit have been exhaustively studied in the literature, covering different areas of volunteering, disaster volunteers have received very little consideration in the same direction (Steerman & Cole, 2009). In general, work environment factors include assigned job (e.g., job workload and job fit), organizational support (e.g., supervisor, training), and relationships with co-workers. These factors have influenced employee and volunteer satisfaction and the intention to stay or quit organizations. Each factor will be examined in the following sections.

Job Fit

Volunteers may stop volunteering because the assigned task does not match their interests or preferences. When a volunteer is not assigned to the right position, they may feel dissatisfied and more likely to quit (Shin & Kliner, 2003). Nonprofit organizations failing to match the volunteers' skills with assignments is one of the reasons volunteers do not return to volunteer for a second year (Eisner, Grimm, Maynard & Washburn, 2009). Consequently, some researchers have used volunteer matching with skills or schedules as a measure to reduce volunteer attrition (Lassiter, Alwahishie & Taaffe, 2014; Gordon, & Erkut, 2004).

Training

Many studies have considered volunteer training as one of the factors that may predict satisfaction and turnover intentions. Ozminkowski et al. (1990) found that volunteers who participated in training were much more satisfied overall with their volunteering experience than those who had not attended. Out of 119 completed questionnaires from volunteers, 48.6% did not report training before performing the job.

As a result, 55.4% of them were dissatisfied with their volunteering experience, while those who received adequate training were highly satisfied, which leads to them continuing their service (Jamison, 2003). A study of hospital volunteers showed that training was among the human resource management (HRM) practices that can influence volunteer satisfaction and attitude (Proença, 2012). Inadequate training does not enhance job skills, which adds to volunteers feeling that they are not performing well within their assigned role (Woodward and Kallman, 2001; Hustinx, 2010; Jamison, 2003; Skoglund, 2006).

Workload

In addition to training, several studies have examined the relationship between workload, satisfaction, and turnover intentions. For example, Sharp (2008) pointed out that workload was among several factors that affect job satisfaction and the intention to leave. Han, Sohn, & Kim (2009) concluded that workload was among the most significant factors in predicting the turnover rate for registered nurses. When a person experiences a heavy workload, this can lead to dissatisfaction and may affect their willingness to continue working in the future. According to Wang, Ellenbecker, & Liu, (2012), the levels of satisfaction and intention to stay for front-line nurse managers can be improved; one of the suggested strategies is to decrease workloads. Also, Elstad (2003) analyzed survey data from 242 active festival volunteers and found that 30% of them were considering quitting, with the most significant factor being workload. Yet, a light workload can also cause dissatisfaction, especially for volunteers who do not feel they are serving the community if they are not being used to the full extent of their volunteer time.

Relationship with volunteers and supervisors

Relationship with a supervisor is another work environment factor that has been identified as a critical factor affecting satisfaction and turnover intentions**.** According to Rice & Fallon (2011), volunteer satisfaction and intention to stay with the organization are primarily influenced by a positive relationship between a volunteer and their immediate supervisor. In a study of 215 respondents from different organizations, Synpniewska (2014) concluded that a positive relationship with supervisors was among the factors that contributed to job satisfaction.

The interpersonal relationships within the volunteer group can be a primary source of dissatisfaction and, hence, turnover. Sometimes volunteers do not feel accepted by their volunteer group, they have a conflict with paid laborers, or they have problems with their supervisors (Hustinx, 2010; Tang, 2010).

Volunteer characteristics

Several studies have considered investigating the possible influence of volunteer characteristics on satisfaction and turnover intentions, such as age, gender, education, and experience. Hurst, Scherer & Allen (2017) used age, gender, amount of time volunteering, and education level as control variables to test their effect on disruptive justice, satisfaction, and turnover intentions. They found that none of the control variables had a signification relationship with dependent and independent variables. Hallmann & Zehrer (2016) noted that gender, education and income were not significantly associated with the overall satisfaction of volunteers. Ramalingam, Sharifuddin, Mohamed, & Ali (2018) tested the difference in volunteer satisfaction with community garden programs between several demographic variables and found that volunteers under 49 years old were less satisfied than volunteers 49 years or older. They also found that male volunteers were more satisfied than female volunteers. Francis & Jones (2012) compared the satisfaction of emergency service volunteers with their organization and found that younger volunteers were more satisfied than their older peers.

Research Questions and Hypotheses:

Based on the empirical evidence found in the literature, several hypotheses were postulated to investigate the relationships among the independent variables (training, workload, volunteer group, supervisor, job-fit, age, gender, education, and experience) and the dependent variables (the intention to stay or quit the organization), with the consideration of satisfaction as a mediator variable. The following are the proposed hypotheses of this study:

1. How do work environment factors predict turnover intentions?

Hypothesis 1: Satisfaction with job fit, workload, volunteer group, supervisor, and training would positively explain the intention to stay and negatively explain the intention to quit.

2. How do work environment factors predict overall satisfaction?

Hypothesis 2: Satisfaction with job fit, workload, volunteer group, supervisor, and training would positively explain overall satisfaction.

3. How does overall satisfaction predict turnover intentions?

Hypothesis 3: Overall satisfaction would positively explain the intention to stay and negatively explain the intention to quit.

4. How do volunteer characteristics predict overall satisfaction?

Hypothesis 4: Age, gender, education, and experiences would positively explain overall satisfaction.

5. How do volunteer characteristics predict turnover intentions?

Hypothesis 5: Age, gender, education, and experiences would positively explain the intention to stay and a negatively explain the intention to quit

Methodology

To address the research questions, a self-administered online survey was sent to disaster volunteers. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used to analyze the data and test the hypotheses.

Participants and data collection

The participants in this study were disaster volunteers, who volunteered with Habitat for Humanity (HFH) or American Red Cross (ARC) within the last five years. The disaster volunteers in this study are not the first respondents who perform, for example, life-saving tasks. Instead, they provide the communities in need with several services, such as cleaning debris, mucking and gutting of homes, building and rebuilding homes, serving people in shelters, and providing medical and relief supplies.

We contracted with Qualtrics to recruit disaster volunteers from HFH and ARC to participate in the study. A total of 390 volunteers completed the survey. Of those responding, 188 disaster volunteers were from HFH, while 202 disaster volunteers were from ARC. Data collection started on 7/7/2017 and ended on 8/8/2017.

Instrument

This research aimed to identify factors that influence disaster volunteers' intentions and ultimately reduce volunteer turnover via the Qualtrics survey. Following the screening question to restrict respondents to those who have worked for HFH or ARC in disasters in the last five years, the participants responded to 20 items that measure work environment factors (job-fit, training, workload, supervisor relation, and group relation), satisfaction, intention to quit, and intention to stay. One 7-point Likert-type scale was used for all items (1 = strongly disagree to 7 = strongly agree). Likert (or ordinal) variables, with at least five categories—seven is better, can often be treated as continuous with no harm to the analysis (Carifio & Perla, 2007; Johnson & Creech, 1983; Norman, 2010; Sullivan & Artino, 2013; Zumbo & Zimmerman, 1993).

Next, the participants responded to the demographic questions that included gender, age, education level, and experience. The survey questions were randomized for all participants, in order to reduce the order bias. Participation in this study was voluntary. All items were adopted from previous work and modified to serve the purpose of this study (Jamison, 2003; Cuskelly, Taylor, Hoye & Darcy, 2006; Malinowski, Keim, Wendt & Weitzel, 2006; de Lara & Tacoronte, 2007; Rowold, Borgmann & Bormann, 2014; Burris, 2012; Vandenberghe & Bentein, 2009; O'Reilly, Chatman & Caldwell, 1991).

Data analysis

After collecting the data from 125 disaster volunteers, we found some cases with straight-lining responses. Straight lining occurs when participants select the same point on the scale across all questions of a survey. Although some researchers consider straight-lining responses as invalid data, and therefore remove them before starting analysis, others propose that there is no clear evidence that such responses are in fact invalid. For this reason, we used attention questions for the rest of our sample (275), and then we compared the same variables between the two groups using a Student's t-test. As we had 20 comparisons, we adjusted the critical p-value using Bonferroni correction to handle the test power issue. The comparisons reveal that there is no difference between the two groups across all variables. Thus, no straight-lining responses were removed from the sample.

One of the major assumptions of the structural equation modeling (SEM) is multivariate normality (Kline, 2015). Therefore, it is important to remove multivariate outliers to avoid multivariate non-normality before conducting a SEM. Multivariate outlier are cases with a strange pattern of scores to several questions (Tabachnick & Fidell, 1996). When data involve several variables, we cannot detect outliers visually and must use algorithms instead (Vakili & Schmitt, 2014). We employed Mahalanobis distance (1936) to check if any multivariate outliers were present in the data set. Mahalanobis distance is a standard distance measure for quantitative data (Bedrick, 2005), and it is commonly used statistical technique that measures how an observation across multiple variables differs from the rest of all observations. A Chi-square statistic was calculated for all Mahalanobis values and compared to the critical value of 45.31, which was calculated based on an alpha level of a 0.001 and degrees of freedom 20 (number of variables). According to Tabachnick & Fidell (2006), any calculated chi-square that is higher than the critical value is to be considered a candidate for being an outlier. The test detected 36 cases; however, after looking carefully at these cases and visualizing the data on a scatter plot, we found that only four data points deviated from the rest of the data points. The four cases (160, 172, 151, 86) were considered outliers and removed from the sample. As a result, a total of 386 disaster volunteers' responses were ready for downstream analysis.

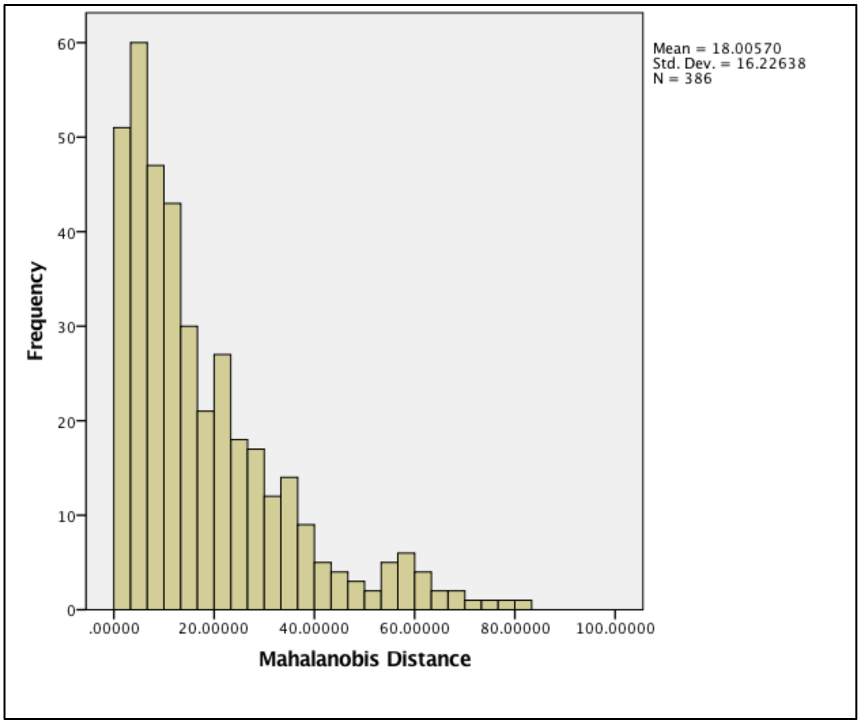

Figure 3. 1 Mahalanobis Distance Values

For assessing the normality of the data, skewness and kurtosis were calculated for all variables. To consider the data as normally distributed, kurtosis should be within ±3 and skewness should within ±2 (Tabachnick & Fidell, 2001). Using SPSS 23.0 for the analysis. We found that the skewness and kurtosis for the data of all variables fell within the acceptable limits of ±2 and ±3, respectively. Therefore, univariate normality was met for all items. Multivariate normality was tested using EQS 6.3. To check the assumption of multivariate normality, we used Mardia's coefficient of multivariate skewness and kurtosis. According to Byrne (2006), Mardia's coefficient is the most widely used to assess the multivariate normality assumption. Bentler (2005) suggested that a value of greater than 5 for Mardia's coefficient is an indication of multivariate non-normality. In the CFA measurement model sections, the results show that Mardia's coefficient is more than 5. Therefore, multivariate non-normality was indicated, and the robust solution was considered.

After that, we again used IBM SPSS 23.0 for data cleaning, preparation, and initial statistical analysis (correlations between the variables and their items). The initial tests revealed that all items significantly correlate with the factors that they measure. Next, we applied structural equation modeling using EQS version 6.3. First, we ran the confirmatory factor analysis CFA to test the measurement model. Next, we conducted the structural model to test the proposed hypotheses.

Result

Respondents profile

Table 3.1 shows the demographic profile from the disaster volunteers responding to the survey. Of the 386 disaster volunteers, 278 were female (72%), and 109 were male (28%). In addition, the age range of the participants was 18-75+ years old. 51% of disaster volunteers were between 25 and 44, and the median age of the participants was 37. Most of the disaster volunteers had high education levels, with 54.4% of the participants holding at least a bachelor’s degree, 31.9% having completed some college (degree/no degree), and 13.5% having completed high school. Only 0.3% of the participants had earned less than a high school degree. With respect to disaster volunteer experience, 26.24% had volunteered for less than a year, 54.4% had volunteered between one and five years, and 19.43% had volunteered for more than six years.

Table 3.1 Frequency Distribution for Demographics

Variable	ARC	HFH (*n2* %)	Overall
	Frequency (%)	Frequency (%)	Frequency (%)
Gender			
Male	59 (29.6)	49 (26.2)	108 (28.0)
Female	140 (70.4)	138 (73.8)	278 (72.0)
Age			
18-24	23 (11.6)	37 (19.8)	60 (15.5)
25-34	54 (27.1)	59 (31.6)	113 (29.3)
35-44	49 (24.6)	35 18.7)	84 (21.8)
45-54	30 (15.1)	28 (15.0)	58 (15.0)
55-64	34 (17.1)	21 (11.2)	55 (14.2)
65-74	8 (4.0)	6 (3.2)	14 (3.6)
75 +	1 (0.5)	1 (0.5)	1 (0.5)
Education level			
Less than high school degree	0 (0)	1 (0.5)	1 (0.3)
High school graduate	23 (11.6)	29 (15.5)	52 (13.5)
Some college but no degree	31 (15.6)	39 (20.9)	70 (18.1)
Associate degree in college (2-	29 (14.6)	24 (12.8)	53 (13.7)
year)	68 (34.2)	65 (34.8)	133 (34.4)
Bachelor's degree in college (4-	32 (16.1)	21 (11.2)	53 (13.7)
year)	7 (3.5)	1 (0.5)	8 (2.1)
Master's degree	9 (4.5)	7 (3.7)	16 (4.1)
Doctoral degree			
Professional degree (JD, MD)			
Experience			
Less than 6 months	31 (15.6)	33 (17.6)	64 (16.6)
7-11 months	23 (11.6)	15 (8.0)	38 (9.8)
1-2 years	43 (21.6)	57 (30.5)	100 (25.9)
3-5 years	59 (29.6)	50 (26.7)	109 (28.2)
6-10 years	22 (11.1)	19 (10.2)	41 (10.6)
Above 10 years	21 (10.6)	13 (7.0)	34 (8.8)
Total	199	187	386

Work environment factors

As seen in Table 3.2, the results of all work environment factors and their items were presented. Overall, disaster volunteers from both organizations were satisfied with all work environment factors. For example, disaster volunteers from ARC and HFH were most satisfied with having good relations with other volunteers in their groups, 5.85 and 5.96 respectively. The second most satisfying experience was that of enjoying working with disaster volunteers in their group 5.78 and 5.91 for ARC and HFH, respectively. In addition, both ARC and HFH disaster volunteers scored the lowest regarding their satisfaction with the pre-service training, 5.39 and 5.10, respectively.

Table 3.2 Descriptive Statistics for Work Environment Factors and Indicators

Indicators and factors	ARC		HFH	
	M	SD	M	SD
Job-fit				
I am satisfied with the fit of the job to my skill	5.55	1.40	5.43	1.53
I am satisfied with the fit of the job to my preference	5.52	1.34	5.37	1.61
I am satisfied with the fit of the job to my schedule	5.52	1.28	5.48	1.53
Training				
I am satisfied with the pre-service training	5.39	1.42	5.10	1.64
I am satisfied with the instructions on the job	5.65	1.23	5.39	1.65
I am satisfied with the onsite training	5.55	1.36	5.35	1.59
Workload				
I am satisfied with my workload	5.48	1.36	5.41	1.64
My workload is about right	5.68	1.19	5.74	1.15
My workload is reasonable	5.73	1.14	5.82	1.11
Volunteer Group Relation				
I am satisfied with volunteers in my group	5.56	1.38	5.49	1.67
I enjoy working with volunteers in my group	5.78	1.20	5.91	1.02
I have good relations with volunteers in my group	5.85	1.19	5.96	1.10
Supervisor relation				
I am satisfied with my supervisor	5.57	1.39	5.50	1.68
I enjoy working with my supervisor	5.69	1.20	5.81	1.19
I have a good relationship with my supervisor	5.74	1.26	5.74	1.16

Overall satisfaction and turnover intentions for disaster volunteers

Overall, the results show that the majority of disaster volunteers were satisfied with their volunteer experience at their organizations 5.76 and 5.96 for ARC and HFH, respectively. With respect to the intention to stay, disaster volunteers at ARC and HFH had high scores for the likelihood of staying with the organization for three years as well as for one year. In addition, disaster volunteers from both organizations scored low in the intention to quit within one year as well as within three years. The results of all items from satisfaction and turnover intentions are shown in Table 3.3.

Table 3.3 Descriptive Statistics for Satisfaction and Turnover Intentions Indicators

Indicators and factors	ARC		HFH	
	M	SD	M	SD
Satisfaction				
Overall, I am satisfied with the volunteer experience at this organization	5.76	1.24	5.98	1.16
Intention to stay				
How likely will you volunteer with this organization for the next year?	5.71	1.31	5.45	1.55
How likely will you volunteer with this organization for the next three years?	5.73	1.33	5.70	1.38
Intention to quit				
I intend to quit the organization in the next year	2.33	1.49	2.37	1.49
I intend to quit the organization in the next three years	2.51	1.58	2.42	1.55

Measurement model

Confirmatory factor analysis (CFA) was carried out to test the relationship between the measured variables (e.g., an item in a survey) and the latent factors (unmeasured variables). In CFA, there are statistical tests that are used to test how well the data fits the proposed model. Among the most recommended tests to report are the

Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). The CFI must be at least 0.95 to show an indication of an excellent fit, while RMSEA has to be less than 0.05 to indicate a very good fit.

<u>The initial first-order measurement model for ARC</u>

Starting with the arc data analysis, the CFA was performed on all factors and their indicators, and the fit indices were obtained. To check the assumption of multivariate normality, we used Mardia's coefficient of multivariate skewness and kurtosis. According to Byrne (2006), Mardia's coefficient is the most widely used for assessing the multivariate normality assumption. Bentler (2005) suggested that a value of greater than 5 for Mardia's coefficient is an indication of multivariate non-normality. The results show the value of 63.9 for Mardia's coefficient, which is an indication of multivariate non-normality. In this case, the robust solution was considered. The output of the CFA reveals unsatisfactory results regarding the fit of the hypothesized model to the data. Even though the CFI-Robust = 0.912, which indicates an acceptable fit, the RMSEA = 0.078 with a 90% CI (0.06, 0.09) reflects a poor fit. After looking closely at the reliabilities and multivariate test statistics, we found that three items were problematic because they are multidimensional. Namely: "I am satisfied with my workload," "I am satisfied with volunteers in my group," and "I am satisfied with my supervisor."

It is recommended to use caution when correcting measurement models to avoid the issue of overfitting. Generally, overfitting means estimating unnecessary parameters that add very little to model fitting (Byrne, 2013; Kenny, 2011). Therefore, it is a tradeoff between estimating additional parameters and achieving a well-fitting model. Removing an item does not cause model overfitting.

An item is removed because it is unreliable (low loading) (Raubenheimer, 2004) or it is multidimensional (Ferrel, 2010). Unreliability has nothing to do with overfitting. Multidimensional items require additional parameters because they share non-target relations. Therefore, removing multidimensional items would reduce the risk of overfitting. The Akaike information criterion (AIC) is a useful measure for selecting the least overfitted model (Burnham & Anderson 2004; Johnson & Omland, 2004). The AIC provides a relative amount of information that is lost when a given model is used to generate data (Akaike, 1974; Hoyle, 2011; Kline, 2010). The model with the lowest AIC score is preferred. For example, a model with AIC=100 is preferred over a model with AIC=180.

The final first-order measurement model for ARC

After deleting the aforementioned items one by one and re-running the measurement model, the results were very satisfying. (S-B $\chi 2$ =89.58, df = 83, CFI = 0.996, RMSEA = 0.020 with CI (0.000,0.045)). In addition, the AIC value has dropped from 28.39 to -76.42, indicating a better model with respect to overfitting. Initial and Final Measurement model results are shown in Table 3.4. Next, model reliability and validity were checked.

Table 3.4 The Goodness of Fit Indices of the First-Order Measurement Model

	S-B χ^2	df	CFI	RMSEA	90% CI (RMSEA)	AIC
Initial measurement model	290.34	131	0.912	0.078	0.066-0.090	28.39
Final measurement model	89.58	83	0.995	0.020	0.000-0.045	-76.42

Reliability and validity

To assess the reliability of the model, the composite reliability (rho) values were subsequently calculated for all factors. Composite reliability is a measure of the internal consistency that indicates the shared variance. As can be seen in Table 3.5, the Rho values ranged from .8 to .936 for all factors, which exceed the recommended value of .7 (Nunnally, 1994), indicating a sufficient model reliability.

To assess the convergent and discriminant validity, the average variance extracted (AVE) for each factor was calculated. Convergent validity is supported if the intercorrelations among items that are supposed to measure the same construct are high, while discriminant validity is supported if the intercorrelations among items that are supposed to measure different constructs are low (Kline, 2011). According to Fornell and Larcker (1981), a high convergent validly of a construct is achieved if its associated AVE is higher than the recommended value of 0.50. Table 5 shows that all AVEs are more than 0.50, indicating a high convergent validity for all constructs. To support the discriminant validity, Fornell & Larcker (1981) suggested that the square root of AVE of a construct must be higher than its correlation with other constructs. Table 3.6 shows the square root of AVEs and the correlations among variables, respectively. The correlations between factors are more than the AVEs for three factors (job fit, workload, and volunteer group relation) indicating a poor discriminant validity.

As seen in Table 3.6, the correlation between job fit and training is 1.0, indicating that these two latent factors are measuring the same construct. Therefore, a second order factor, volunteer-job fit, was created to represent job fit and training. Also, the intention to stay and the intention to quit were highly correlated. Therefore, a second order factor, turnover intentions, was created to represent the two factors after reversely coding the intention to stay. In addition, all correlations among the factors were high, meaning that the concept of work environment is reflected by all factors. Hence, a work environment factor was created to include all factors (Table 3.7).

Table 3.5 Final First-Order Factor Measurement Model

Indicators and factors	Standardized loadings	Rho	AVE
Job Fit		0.899	0.749
I am satisfied with the fit of the job to my skill	0.865		
I am satisfied with the fit of the job to my preference	0.873		
I am satisfied with the fit of the job to my schedule	0.858		
Training		0.910	0.770
I am satisfied with the pre-service training	0.859		
I am satisfied with the instructions on the job	0.885		
I am satisfied with the onsite training	0.889		
Workload		0.894	0.808
My workload is about right	0.910		
My workload is reasonable	0.888		
Volunteer Group		0.835	0.718
I enjoy working with volunteers in my group	0.798		
I have good relations with volunteers in my group	0.894		
Supervisor		0.913	0.840
I enjoy working with my supervisor	0.919		
I have a good relationship with my supervisor	0.914		
Intention to stay		0.891	0.803
How likely will you volunteer with this organization for the next year?	0.871		
How likely will you volunteer with this organization for the three years?	0.921		
Intention to quit		0.936	0.880
I intend to quit the organization in the next year	0.889		
I intend to quit the organization in the next three years	0.985		

Table 3.6 Average Variance Explained (AVE) and Factor Correlation Matrix for ARC

Measures	F1	F2	F3	F4	F5	F6	F7
F1	0.865						
F2	1.000	0.877					
F3	0.754	0.720	0.899				
F4	0.726	0.696	0.957	0.847			
F5	0.674	0.630	0.887	0.929	0.917		
F6	0.446	0.457	0.627	0.657	0.626	0.896	
F7	-0.398	-0.415	-0.566	-0.527	-0.482	-0.835	0.938

a. The diagonal elements represent the square root of the average variance extracted.
b. The off-diagonal elements are the correlations between factors
c. Note: F1= Job Fit; F2= Training; F3 = Workload F4 = Volunteer Group; F5= Supervisor; F6= Intention to Stay; F7 =Intention to Quit.

The revised second-order measurement model

Second-order factors have less than or equal to the number of estimated parameters to the first order factors. Therefore, adding second-order factor are never overfitting. Second-order factor is useful in reducing collinearity and producing models that explain data with a minimum number of parameters (Kenny,2016).

After creating a work environment factor that included all factors, the results indicate that the CFA for ARC shows excellent fit (S-B χ^2 =107.24, df =97, CFI =0.993 and RMSEA = 0.0230 (0.000,0.045)). Next, using the same measurement model structure for HFH organization results in a very good fit without the need of estimating extra parameters (S-B χ^2 =129.52, df =97, CFI =0.98 and RMSEA = 0.042 (0.019,0.060)). THE values of AIC for the second order factor of ARC and HFH are -86.76 and -64.48

respectively. These values indicate that creating second-order factors do not cause overfitting.

Table 3.7 The Second-Order Factor Measurement Model

Indicators and factors	ARC			HFH		
	Standardized loadings	Rho	AVE	Standardized loadings	Rho	AVE
F8: Volunteer Job-Fit		1.000	1.000		0.992	0.985
F1: Job fit	1.000			0.992		
F2: Training	1.000			0.993		
F9: Work Environment		0.950	0.827		0.925	0.761
F3**:** Workload	0.970			0.948		
F4: Volunteers in Group	0.993			0.989		
F5: Supervisor	0.921			0.905		
F8: Volunteer Job-Fit	0.730			0.591		
F10: Turnover intentions		0.911	0.837		0.926	0.863
F6: Intention to stay*	-0.901			-0.925		
F7: Intention to quit	-0.929			-0.933		

*F6 is reversely coded

Configural model

One way to check the group invariance is to test the configural model. In the configural model, both organizations' second order models were tested simultaneously, without constraints. If the results of the configural model are satisfactory, then one can say the two organizations are invariant. In contrast, if the configural model shows a misfit, further analysis should be conducted to ascertain if there is a partial invariance between the two groups (Byrne, 2006).

The configural model for HFH and ARC output indicates satisfying results. These results provide evidence that there is no difference between the two groups (Table 3.8).

Table 3.8 The Goodness of Fit Indices of Second-Order Measurement Models and Configural Model

	S-B χ^2	df	CFI	RMSEA	90% CI (RMSEA)	AIC
ARC	107.24	97	0.993	0.023	0.000-0.045	-86.76
HFH	129.52	97	0.980	0.042	0.019-0.060	-64.48
Configural model	234.30	194	0.987	0.033	0.012-0.047	-153.7

Structural model

The structural equation model (SEM) is estimated using the maximum likelihood estimation under the assumption of multivariate normality for the data (Byrne, 2006). Mardia's standardized coefficient was used to assess the multivariate normality, with a coefficient (86.228) greater than the criteria of 5, which indicates that the data is multivariate non-normally distributed (Byrne, 2006). As a result, a robust maximum likelihood method was used. The structural model fit indices indicated that the model fit the data very well (S-B $\chi 2$ =141.50, df = 109, CFI = 0.990, RMSEA = 0.028 (0.012,0.040)).

Comparing group difference on dependent variables

Before generalizing research findings on the volunteers from both organizations, we tested whether there was a difference between the two organizations regarding satisfaction and turnover intentions. A 0-1 variable was used as an independent variable that predicts both overall satisfaction and turnover intentions. The results revealed no significant difference in both predicted variables between HFH and ARC disaster volunteers. Next, structural modeling was performed for the full sample without the group number variable.

Structural model regression

Table 3.9 presents the direct and indirect effects between the work environment, overall satisfaction, and turnover intentions. For the direct effects, work environment had a significant direct effect on both overall satisfaction (B=0.798) and turnover intentions (B=0.380). Also, overall satisfaction significantly predicted turnover intentions (B = 0.315). For the indirect effects, work environment significantly influenced turnover intentions through overall satisfaction. Table 3.10 and Table 3.11 show the lower order effects on overall satisfaction and turnover intentions.

Table 3.9 The Effect of Work Environment on Satisfaction and Turnover Intentions

Direct effects	Standardized Solutions	Unstandardized Solutions
F9 → F10	.795	.950
F9 → F11	-.355	-.395
F10 → F11	-.325	-.303
Indirect effects		
F9 → F10 → F11	-.258	-.288

Note: F9= Work Environment; F10= Overall Satisfaction; F11 = Turnover intentions

Table 3.10 The Relationships of Lower-Order Factors with Overall Satisfaction

Lower-order factor effects	Standardized regression coefficients	Unstandardized regression coefficients
F8 → F9 → F10	.517	.782
F1 → F8 → F9 → F10	.515	.782
F2 → F8 → F9 → F10	.515	.796
F3 → F9 → F10	.764	.942
F4 → F9 → F10	.791	.860
F5 → F9 → F10	.716	.953

Note: F1= Job Fit; F2= Training; F3 = Workload F4 = Volunteer Group; F5= Supervisor; F6= Intention to Stay; F7 =Intention to Quit; F8: Volunteer Job Fit; F9= Work Environment; F10= Overall Satisfaction

Table 3.11 The Relationships of Lower-Order Factors with Turnover Intentions

Lower-order factor effects	Standardized regression coefficients	Unstandardized regression coefficients
F8 → F9 → F11	-.231	-.325
F8 → F9 → F10 → F11	-.165	-.237
F1 → F8 → F9 → F11	-.230	-.325
F1 → F8 → F9 → F10 → F11	-.164	-.237
F2 → F8 → F9 → F11	-.230	-.331
F2 → F8 → F9 → F10 → F11	-.164	-.241
F3 → F9 → F11	-.341	-.392
F3 → F9 → F10 → F11	-.248	-.286
F4 → F9 → F11	-.353	-.357
F4 → F9 → F10→ F11	-.257	-.287
F5 → F9 → F11	-.323	-.396
F5 → F9 → F10→ F11	-.235	-.289

Note: F1= Job Fit; F2= Training; F3 = Workload F4 = Volunteer Group; F5= Supervisor; F6= Intention to Stay; F7 =Intention to Quit; F8: Volunteer Job Fit; F9= Work Environment; F10= Overall Satisfaction; F11 = Turnover intentions

The influence of demographic information on model relationships

The next step was to compare the structural model before and after, using gender, age, education, and experience as control variables. As seen in Table 11, the results suggest that gender, age, and education do not influence satisfaction and turnover intentions. The results also indicate that experience has a positive significant effect on turnover intentions. This means that a volunteer's experience has a positive impact on the intention to stay, and a negative impact on the intention to quit. However, experience can be seen to have no effect on overall satisfaction.

Table 3.12 The Effect of Disaster Volunteer Characteristics on Satisfaction and Turnover intentions

	Dependent variables					
Independent variables	Satisfaction R^2= 0.637			Turnover intentions R^2= 0.464		
	B(SE)	Beta	Z-score	B(SE)	Beta	Z-score
Gender	.171(.097)	.064	1.765	-.048(.108)	-0.019	-.442
Age	.042(.082)	-.018	-.518	.105(.094)	0.047	1.123
Education	.024(.079)	-.01	-.298	-.017(.093)	-0.008	-1.79
Experience	.020(.040)	.019	.508	.218(.048)	0.212	4.56.

Discussion

This study extended the current research on volunteerism in disasters by investigating the effect of work environment factors on satisfaction and turnover intentions of disaster volunteers, in two US relief organizations. Several hypotheses were developed and tested using structural equation modeling. The results of this study indicate that the satisfaction with work environment factors does impact overall satisfaction and turnover intentions.

The findings of this study supported hypotheses 1, 2, and 3: the satisfaction with work environment factors has a significant positive impact on overall satisfaction and a negative significant effect on turnover intentions. Specifically, satisfaction with workload, relationship within a volunteer group, and relationship with the supervisor have the highest impact on satisfaction, intention to stay and intention to quit, followed by job fit and training.

As hypothesized, satisfaction with interpersonal relationships correlates with satisfaction and turnover intentions. It was found that the satisfaction within volunteer groups and supervisor has a positive significant relationship with satisfaction and intention to stay, and a negative significant relationship on the intention to quit. Hustings (2010) found that interpersonal relationships among volunteers was a main source of dissatisfaction. Several respondents who decided to quit the organization stated that the main reason was the negative atmosphere within the volunteer group. Among the reasons that hampered volunteers' enthusiasm was gossip, quarreling, lack of team spirit, envy, and unhealthy competition. According to Rice & Fallon (2011), a positive relationship between a volunteer and their immediate supervisor was one of the main factors that increased volunteer satisfaction and intention to stay with the organization.

Consistent with our hypotheses, we found that satisfaction with workload is positively related to satisfaction and negatively related to turnover intentions. Similarly, dissatisfaction with workload has a significant negative relationship with satisfaction and a significant positive relationship with turnover intentions. This finding is consistent with previous work (Sharp, 2008; Ellenbecker, & Liu, 2012; Elstad, 2003). Excessive workload may lead to dissatisfaction and turnover intentions by exhausting a volunteer's physical energy, emotional well-being, or even their health. Conversely, a light workload may cause dissatisfaction and turnover intentions because the valuable time of the volunteers is being wasted and not being used optimally.

The findings also support the hypothesis that both satisfaction with job fit and training have a significant positive impact on satisfaction and a significant negative impact on the turnover intentions. This finding is also consistent with the literature. Failure to place volunteers in the right position, based on their skills, leads to high levels of dissatisfaction and results in high turnover (Shin & Kliner, 2003; Eisner, Grimm, Maynard & Washburn, 2009). Adequate training enhances satisfaction and intention to stay with the organization; the inverse is also true (Jamison, 2003; Skoglund, 2006).

The results of this study also support the third hypothesis. A higher level of satisfaction when volunteering during a disaster with the organization has a negative impact on the turnover. This finding is consistent with the previous research on volunteerism (Ellenbecker, 2004; Steijn, 2005; Vecina, Chacón, Sueiro, & Barrón, 2012).

The findings do not support most of hypotheses 4 and 5. Age, gender, and education level do not have a significant impact on satisfaction and turnover intentions. These findings are consistent with previous studies (Hurst, Scherer & Allen, 2017;

Hallmann & Zehrer, 2016). However, conflicting results arise from other studies, where age and gender do impact satisfaction (Ramalingam, Sharifuddin, Mohamed, & Ali, 2018; Francis & Jones, 2012).

Volunteer experience, however, was found to negatively impact the turnover intentions. Disaster volunteers with more than one year of disaster experience were more likely to stay with an organization than volunteers with less than one year of experience. In addition, disaster volunteers who have volunteered for at least six years have the highest amount of intention to stay with the organization.

There are some limitations to this study. The study focused on only two organizations to recruit a reasonable number of disaster volunteers. Consequently, the results of this study have a generalizability issue. Future research could expand the potential sample by working directly with organizations to recruit their disaster volunteers. In addition, this study employed a cross-sectional survey, which captured responses from disaster volunteers at a single point in time. This work did not examine changes in volunteer satisfaction with work environment, satisfaction, and turnover intentions over time. It would be more beneficial to conduct multi-stage longitudinal studies that monitor volunteers from the time they start volunteering, until they decide to leave the organization. However, such data collection strategies were beyond the scope of this research.

It would be beneficial for relief organizations to adopt practices that improve elements of the work environment, specifically, the relationship with volunteers, the relationship with supervisors, and the workload. These practices will contribute to increasing volunteer satisfaction and intention to stay, while reducing intention to quit. Improving training and job fit will also have a considerable effect on volunteer satisfaction and turnover intentions.

The findings of this study could be used by researchers to develop analytical tools that improve staffing in disaster relief events, with the consideration of volunteer behavior and work environment. Due to the complexity of the problem, simulation models are an appropriate tool for handling such complexity. The findings of this study are required for estimating the effect of job-fit, training, workload, and interpersonal relationships on satisfaction and turnover intentions for disaster volunteers. For example, when there are conflicting ideas or relationship tensions within a volunteer group, the satisfaction of volunteers within the group could be reduced. Consequently, the overall satisfaction and turnover intentions could be affected. These effects can be estimated using the prediction equations from this work. Agent-based modeling could be used to model group behavior, where volunteers are agents and their interaction within a group can be modeled using state charts.

Conclusion

The purpose of this work was to study the effect of work environment on satisfaction and turnover intentions for disaster volunteers in two US relief organizations, American Red Cross and Habitat for Humanity. To accomplish this, confirmatory factor analysis and structural equation modeling were conducted. The findings suggest that work environment positively influences overall satisfaction and intention to stay, but negatively impacts the intention to quit. In other words, when disaster volunteers are satisfied with their work environment, they are willing to stay with the organization. Also, it was found that among the work environment indicators, satisfaction with the supervisor and the volunteer group, and workload, have the highest effect on satisfaction and turnover intentions, followed by job fit and training.

The results also found that the age, gender, and education level have no effect on satisfaction and turnover intentions. However, previous disaster volunteer experience does have a significant positive effect on turnover intentions. Volunteers with more years of experience are more likely to stay with an organization than other volunteers.

Based on the findings of this study, we recommend decision makers within relief organizations consider increasing efforts in improving group atmosphere and workload, followed by improving volunteer job matching and training. Doing so will have a positive impact on disaster volunteers' overall satisfaction and turnover intentions, which in turn will improve their retention and reduce turnover.

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CHAPTER 4

DISASTER VOLUNTEER MANAGEMENT AND BEHAVIOR MODEL: A SIMULATION APPROACH

Introduction

In order to help NGO decision makers, manage their volunteers effectively, a range of quantitative models have previously been developed to handle volunteer assignment, all of which are optimization models designed to find solutions to an assignment problem. Unlike for these previous models, in this chapter we are interested in tracking individual behavior in response to work environment factors during relief efforts, such as assignment matching/mismatching, workload, and group conflict. In addition to work environment factors, considering the characteristics of volunteers' satisfaction levels and turnover intentions add a great deal of complexity to the assignment problem, making it almost impossible to use mathematical models. Agent based simulation modeling, on the other hand, is a very appropriate tool for modeling such complex systems. While there is variety of applications for agent-based modeling in different fields, only one study was found regarding volunteer behavior in relief efforts (Linder, Kühnel, Betke & Sackmann, 2018).

The purpose of this chapter is to develop a simulation model that is able to handle such complexities. We are proposing an agent-based simulation model to help decision makers at NGOs assign their volunteers to different tasks effectively in order to serve community needs after disasters, and to monitor volunteer satisfaction levels and intentions to quit to ensure higher levels of retention. Two types of information are necessary to create a realistic simulation model for a relief event: knowledge from disaster volunteer managers about how they manage volunteers, and knowledge from disaster volunteers about how their satisfaction levels and intentions to quit are explained by work environment factors. In this study, we explore how volunteers are managed in disasters by conducting an online survey with 14 disaster volunteer managers. The findings from the previous chapter are used to model volunteer behavior.

Literature review

For volunteer scheduling, Gordon and Erkut (2004) developed a spreadsheet-based decision support tool to generate shift times and schedule volunteers for the Edmonton folk music festival. They used integer programing formulation to handle the task preferences with the goal of minimizing the number of surplus volunteers. In one study, Sampson (2006) demonstrated how volunteer labor assignment (VLA) problems are quite different from traditional labor assignment (TLA) problems. He considered the volunteer as a laborer with no cost which he incorporated into a goal programming model. In VLA, the goal was to minimize the total cost of assigning excessive volunteers, assigning too few volunteers, the actual volunteer assignments, and unsatisfied task Demand. In addition, Falasca, Zobel and Fetter (2009) developed a multi-criteria optimization model to help assign volunteers to tasks. As with Sampson (2006), they reviewed the differences between a volunteer labor assignment and a traditional labor assignment. In another study, Falasca, Zobel and Ragsdale (2011) discussed the creation of a spreadsheet multi-criteria volunteer scheduling model to help a small development organization in a developing South American country. The goal of the model was to reduce the number of unfilled shifts, minimize the total scheduling costs, and minimize undesired assignments. This study was different from Sampson (2006) in that it considered volunteer labor cost as non-negligible. Finally, Lassiter, Taaffe, and Alwahishie (2014) developed a mixed integer programming model to help humanitarian organizations assign volunteers to different task skills. This model is the first one to consider volunteer training to help other volunteers with a different task skill-level. They considered different probabilistic demand scenarios and studied how the model responded to such uncertainties by assigning volunteers to different tasks. They found that preemptive training, even at the cost of not meeting a current need, can increase the ability to meet the anticipated work required in future periods. Mayorga, Lodree, and Wolczynski (2017) modeled spontaneous volunteers' assignments problem as a continuous time Markov decision process that can be applied to stable work during recovery efforts.

People characteristics and behavior add a great deal of complexity to the assignment problem which makes mathematical models almost impossible to be used. Simulation modeling, on the other hand, becomes a very attractive tool to model such complex systems. Linder, Kühnel, Betke, and Sackmann (2018) developed a conceptual model for spontaneous unaffiliated on-site volunteer behaviors. The behaviors in their conceptual model include the intention to volunteer, the motivation, and the need to help. They also implemented the conceptual model in Anylogic simulation software and used different volunteer attributes to predict volunteers' behaviors under different circumstances. This research has three main objectives:

1. Conduct a questionnaire to explore how disaster volunteer managers make managerial decisions.
2. Propose a simulation model with discrete event and agent-based components to represent a disaster relief event, in which the management practices from the managers' surveys could be implemented and the disaster volunteers' behaviors could be predicted.
3. Using a numerical example, based on the managers' survey data as well as the disaster volunteer survey data, analyze how disaster volunteers' behavior is predicted by their work environment while they are serving a community in need.

Methods

This section introduces the disaster volunteer manager survey, present disaster volunteer behavior findings from previous chapter, and then proposes the simulation model to be used in this study.

Disaster volunteer manager survey

To build a realistic model for a disaster relief event, it is vital to obtain relevant information from experts in the field. To do so, we conducted an online survey with 14 disaster volunteer managers from Red Cross and Habitat for Humanity, 7 managers from each organization. The questions in the survey cover three different topics: disaster volunteers, disaster volunteer management, and disaster relief events. The same seven-point Likert-type scale was used for all items (1 = Never to 7 = Always). The participants' responses are summarized in the following sections.

Disaster volunteer management

The surveyed disaster volunteer managers responded to questions about how they handle situations where they have an excess or shortage of volunteers available during the week of a relief event. Generally, in the case of having extra volunteers, the managers indicated that they are more inclined to distribute the workload among the available volunteers or provide some people with non-essential jobs than to turn them away (Table 4.1).

Table 4.1 Managing the Surplus of Volunteers

Indicators and factors	M	SD
Managing Extra Disaster Volunteers		
Turn them away	2.43	1.22
Provide them with non-essential jobs	3.79	1.25
Redistribute the workload among all volunteers	4.64	1.45

Notes: Scale values range from 1 ("Never") to 7 ("Always").
M = mean, SD = standard deviation

When there is a shortage of disaster volunteers, managers seem to be slightly more inclined to work with the available team and maybe ask them to take on more of the workload, rather than to reach out to other organizations. However, if there is a situation where they ask other organizations to provide them with volunteers, they have a higher likelihood (M = 4.6) of getting enough volunteers than not (Table 4.2).

Table 4.2 Managing the Shortage of Volunteers

Indicators and factors	Red Cross	
	M	SD
Managing a Shortage of Volunteers		
Reach to other organizations to get enough volunteers	4.50	1.34
Put on more workload on existing volunteers	4.43	1.09
Work with existing volunteers and wait for more volunteers to come	4.64	1.01
Requesting volunteers from other organizations		
When you reach to other organizations to get volunteers, how often that you get enough disaster volunteers?	4.31	1.18

Notes: Scale values range from 1 (“Never”) to 7 (“Always”).
M = mean, SD = standard deviation

To understand how disaster volunteer managers, assign tasks to volunteers during a relief event, we posed three questions. The first question is about the criteria used to select volunteers to handle a specific task. The results suggest that disaster managers are more likely to use volunteers’ skills and preferences to match them to specific jobs, rather than to select volunteers randomly to perform the available tasks. The second question focuses on how to manage assignments among volunteers who have just arrived to help and those who are already working. Disaster volunteer managers at the Red Cross tend to slightly prefer assigning the available jobs to the arriving volunteers over redistributing the tasks among all volunteers. Managers from Habitat for Humanity use both strategies with equal weight. The last question considers moving volunteers between sites to handle volunteer shortages and get the necessary work done. The results indicate that managers from both organizations are more likely to move volunteers around to satisfy the community's needs than not. Table 4.3 summarizes these results.

Table 4.3 Volunteer Assignments

Indicators and factors	Red Cross	
	M	SD
Volunteer assignment criterion		
Volunteer skill level	5.07	1.49
Volunteer preferences	4.79	1.37
Randomly assign volunteers to available tasks	3.50	1.34
Managing volunteers		
New Arriving Volunteers get assigned to the available work opportunities.	4.71	1.07
Redistribute the existing and the new volunteers to the available jobs	4.50	0.85
Moving volunteers between sites		
If there is a shortage of volunteers at one site and extra volunteers at other sites, how often do you move volunteers between sites to complete the work?	4.23	0.84

Notes: Scale values range from 1 ("Never") to 7 ("Always").
M = mean, SD = standard deviation

Disaster volunteer information

The disaster volunteer managers also responded to questions related to disaster volunteers' information, such as volunteering time, volunteer skills and preferences, signing up, arrival patterns, and reasons of conflict.

Volunteering time

According to our survey data, there is considerable variance between the amount of time committed by disaster volunteers, ranging from one day per week for two weeks, to seven days a week for four months. From the managers' experience, volunteering time generally ranges from less than a week to 20 weeks; however, some volunteers leave early and do not fulfil all the time they originally committed to. Table 4.4 shows the volunteering time based on their commitment type.

Table 4.4Volunteering Time (Weeks)

Commitment type	M	SD
Short-term commitment	3.57	3.20
Long-term commitment	7.29	5.57

Skill levels

The responses from the disaster volunteer managers regarding the skill sets indicate that the number of volunteers with few skills and those who are highly skilled is about the same.

Table 4.5 Volunteer Skill Levels

Commitment type	M	SD
Skill I (Volunteers with few skills)	52.7%	22.2
Skill II (Volunteers with many skills)	47.3%	22.2

Volunteer arrival

The number of volunteers arriving every week is somewhat unpredictable. However, the managers informed us about the most likely scenario for volunteer arrivals. This involves volunteers arriving in relatively small numbers at the beginning of the relief event, with numbers increasing week by week until they reach a peak. After that point, the number of volunteer arrivals starts declining until the end of the relief event.

Table 4.6 Disaster Volunteers Arrival Patterns

Arrival scenarios	M	SD
The number of arriving volunteers is large at the beginning of the disaster relief event, and gradually decreases until the end of the disaster relief event.	4.71	1.59
The number of arriving volunteers is small at the beginning of the disaster relief event, and gradually increases until the end of the disaster relief event.	3.43	1.22
The number of arriving volunteers is small at the beginning of the disaster relief event, and gradually increases to a peak until the middle of the disaster relief event, then decreases again until the end of the disaster relief event.	4.36	1.22

Volunteer conflict

The disaster volunteer managers rated the reasons that may lead to conflict among disaster volunteers. Table 4.7. Shows the scores of each reason. Overall, the results indicated that there is no obvious difference among these reasons. Disaster volunteer managers from Red Cross tend to score higher in the difference in age than with the rest of the reasons.

Table 4.7 Reasons of Conflict among disaster volunteers

Reason of conflict	M	SD
Difference in age	3.93	1.14
Difference in skill level	3.93	1.07
Difference in education level	3.50	1.29
Difference in experience	3.71	1.20
Difference in workload	3.93	1.07

Disaster volunteer behavior

Understanding disaster volunteer behavior is a vital component in developing a simulation model for a relief event. The survey information and findings from Chapter 3 were used to derive the prediction equations needed for this study. We used the structural equation model from Chapter 3 to obtain the regression equations for the volunteers' overall satisfaction and turnover intentions.

We transformed all latent variables (variables with two items or more) into measured variables by calculating the average score of their items. To determine the values for intention to participate for each disaster volunteer, we then used SPSS 23.1 to conduct a linear regression using data collected from the survey in Chapter 3; the dependent variable was overall satisfaction, measured on a seven-point Likert scale, and the independent variables included work environment, age, gender, experience, and education. A significant regression equation was found ($F [5,380] = 99.036$, $p < 0.000$), with an R^2 of 0.752. The overall satisfaction increased by 0.893 for each unit increase in the work environment, and females were 0.227 times more satisfied with the organization than males were. Both work environment and gender were significant predictors of overall satisfaction. The regression equation of the overall satisfaction is as follows:

$$Overall\ satisfaction = 0.645 + 0.893 \times (work\ environment) + 0.227 \times (gender) \quad (4\text{-}1)$$

In addition, we conducted a linear regression using data collected from the survey in Chapter 3, with the turnover intentions on a seven-point Likert scale being the dependent variables, and the overall satisfaction, work environment, age, gender, experience, and education as the independent variables. A significant regression equation was found (F [6,379] = 45.726, $p < 0.000$), with an R2 of 0.648. Behavioral intentions decreased by 0.376 for each unit increase in the work environment and decreased by 0.257 for each unit decrease in the experience level and decreased by 0.388 for each unit increase in the overall satisfaction. Work environment, overall satisfaction, and experience were significant predictors of turnover intentions. The regression equation of the turnover intentions is as follows:

$$Turnover\ intention = 7.148 - 0.376 \times (work\ environement) - 0.257 \times (experience) - 0.388 \times (overall\ satisfaction) \tag{4-2}$$

Using the structural equation model in Chapter 3, we also determined the relationships between the work environment factors and the dependent variables by multiplying the effect sizes that lead from each factor to the dependent variable. The following equations are the ones in which the values of the overall satisfaction and the turnover intentions, in Equations 4-1 and 4-2, change as a result of the volunteers' satisfaction with the experience:

$$Overall\ oatisfaction = overall\ Satisfaction + .780 * job\ fit + 0.942 * workload + .860 * volunteer\ group \tag{4-3}$$

$$Turnover\ intenti = \ turnover\ intention - .562 * job\ fit - .678 * workload - .644 * volunteer\ group \quad (4\text{-}4)$$

Simulation model for a relief event

One approach to this problem would be to propose a mathematical programming formulation in which the periodic supply (i.e., volunteers and their skill levels) is allocated to the demands (i.e., the community's needs). In this case, forecasts of volunteer arrivals and community needs would be estimated and represented as unique scenarios. Initial research with such a model has been explored by Lassiter et al. (2014). While there is much to be learned from this kind of approach, a key limitation is the way in which an individual is characterized. The model cannot accurately assign and un-assign specific volunteers, while also correctly tracking individual volunteers' satisfaction levels and turnover intentions due to their assignments, without adding indices to specify each volunteer explicitly. Group conflict, where volunteers communicate with others in the group, adds further complexity to the issue of formulation. This kind of problem lends itself very readily to an agent-based (AB) simulation approach. For this research, we have developed a hybrid (DE-AB) simulation model in the AnyLogic 8.5 simulation programming language.

In the simulation model, the main component is the agent itself, and because we are dealing with volunteers who have different skills, an agent class is created to represent the volunteers. Volunteer assignments and volunteer behavior are captured by state charts, which represent the possible states and transitions that a specific volunteer may experience. It is within the state chart that we can specify the policy that will govern how volunteers will be managed.

The model consists of two modeling methods: a discrete event approach and an agent-based approach. The agent-based section (Figure 4.1) is responsible for registering volunteer arrivals, updating their demographic information, updating their satisfaction levels and turnover intentions, and updating their group behavior. When disaster volunteers arrive, they are added to the state "Arrivals," where their information is updated. Probability distributions are used to determine age, gender, education level, and level of experience. In addition, a normal distribution is used to determine how satisfied a given disaster volunteer is with their work environment currently. The values of the demographic variables and the work environments are used in prediction equations to determine the current level of satisfaction and turnover intentions.

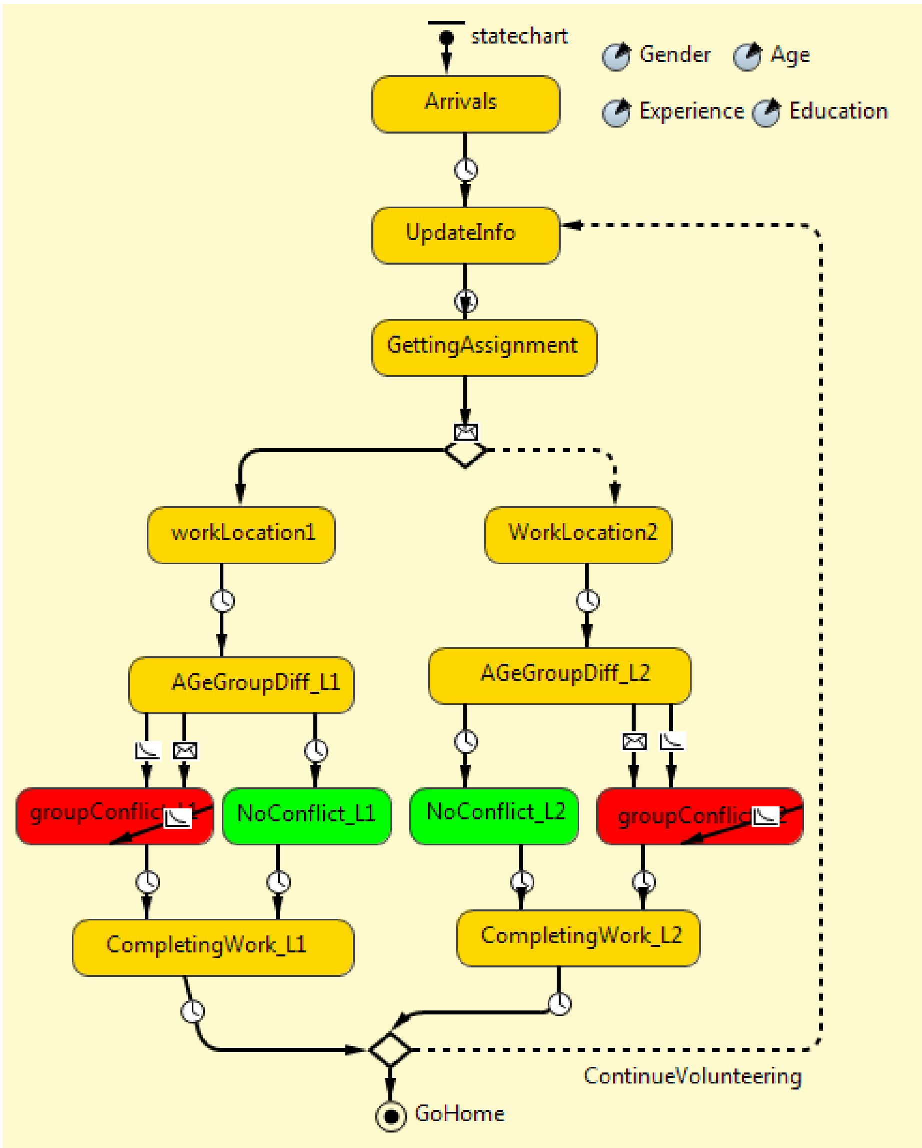

Figure 4.1 Disaster Volunteer Management Model

The disaster volunteers (agents) then enter the discrete event using a message. Once they enter the discrete event (Figure 4.2), they are given an assignment based on the available opportunities and the number of disaster volunteers available.

Disaster volunteers who receive an assignment that matches their skills and preferences will be more satisfied and less likely to quit, while those who are mismatched with an assignment will be dissatisfied, and their turnover intentions will increase accordingly. Other volunteers may not receive an assignment. Instead, they will be asked to stay at the location and carry out non-essential tasks. This will cause dissatisfaction with their workload, which will also impact their overall level of satisfaction and turnover intentions. After a volunteer is given a task assignment and a location to go to, they will return to the agent-based section via messages. Next, they will start working at their location. From this point, group conflict could happen; for example, a volunteer may cause a problem and affect others in the group. Not all volunteers will be affected, but for anybody who is impacted, their satisfaction and turnover intentions will be revised and updated based on regression equations from the structural modeling work presented in the previous chapter.

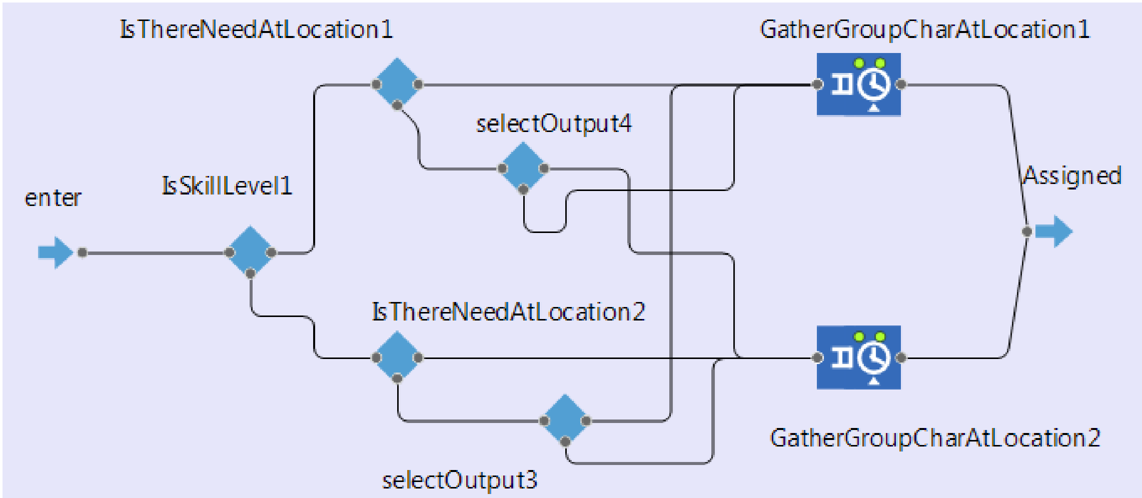

Figure 4.2 Volunteer Assignment and Workload

After completing their first week of work, disaster volunteers will go back to the "updateInfo" state to try to find another volunteering opportunity. They will continue working until their committed time is over, at which point, they will move to the "GoHome" Node.

Model assumptions and settings

Interactions between volunteers in group and their behavior

In the volunteer manager survey, the responses from disaster volunteer managers at Red Cross, indicated a high score for the "difference in age" between members of a volunteer group as a cause of conflict. To reflect this in the model, messages and rates were created to cause a conflict in the group. The group satisfaction score in the disaster volunteer survey was 5.815 out of 7, which means that disaster volunteers are about five times more satisfied with their group than not. Therefore, we assume that the chance of a disaster volunteer to get into a conflict with the group is about 0.2. Here, we use a rate of one per week for volunteers causing a conflict while we use a rate of one fifth per week for volunteers who do not have any conflict. Next, we applied an internal link inside the state "groupConflict" to send a message to the volunteers in the group. Since difference in age is among the highest reasons for group conflict, we considered the standard deviation of volunteer ages as the contact rate between volunteers to deliver the conflict. If the volunteers in the group were in the same age category, then the standard deviation will be zero and no message will be sent. Otherwise, a message will be sent with a rate that is equal to the standard deviation of the volunteer ages in that group. When the message is sent, any member of the group could be affected, and their satisfaction level and turnover intentions were updated accordingly using the prediction equations.

As described above, the model allows for the satisfaction level and turnover intentions to increase or decrease based on a volunteer's experience in each week. If a volunteer receives a matched assignment and a suitable workload or experiences no conflict in their group, their satisfaction will increase by their regression coefficient in the prediction equation. Their satisfaction will be reduced by the same amount if they are mismatched, are assigned no workload, or are affected by a conflict in their volunteer group.

Regression equations used in the simulation

We used Equations 4-1 and 4-2 to determine the initial values of satisfaction and the turnover intentions at the beginning of the simulation. After each week of assignments, disaster volunteers may feel either satisfied or dissatisfied with their job fit, workload, and volunteer group. As a result, their satisfaction and turnover intentions are updated using Equations 4.3 and 4.4.

Experiments/settings

1. 386 disaster volunteers will either have skill 1 (55.2 %) or skill 2 (44.8%) based on averages from survey results.
2. Volunteer arrival Scenarios I & II will be the most-selected pattern in the survey as indicated previously in Table 4.6.
3. Skill 1 and skill 2 community needs will mostly overlap in the middle of the relief event. The community need for skill 1 will be higher at the beginning and lower at the end.
4. Each scenario will be run using capacity levels (0.5, 1, 1.5, and 2). The capacity level (CL) is the ratio of the number of volunteers to the number of volunteers needed (unmet community needs).
5. Volunteers will not be sent away if they have no workload. It is assumed that they will stay and carry out non-essential jobs (no workload), which will cause a negative workload effect on their satisfaction and turnover intentions.
6. In each arrival scenario, in addition to the base-case, two more experiments were conducted considering moderate and high group conflict.
7. Disaster volunteers (existing and new arrivals) will be redistributed every week based on their skill levels.
8. The model will run for 20 weeks with 100 ruplications, starting with a random seed.

Results

Table 4.8 shows the satisfaction and turnover intentions result for Scenario I. Satisfaction values are high across all capacity levels (CLs), with a small decrease at the CL of 2. The turnover intentions slightly increase at CL = 1 and increase more at the CL of 1.5 and 2. The unmet needs value is very high at CL = 0.5 and drops to 2.3 as the CL increases. This scenario assumes that volunteers who have no work will stay at their location and carry out non-essential jobs if there are any. At CL = 1.5, more volunteers are available to help, but when there is no work, the number of volunteers who stay with almost no job increases. Their satisfaction is negatively impacted due to dissatisfaction with their workload. In Tables 4.9 and 4.10, we consider cases in which more conflict levels are introduced. Satisfaction drops quickly when moderate conflict is introduced and drops drastically when high group conflict is presented. Similarly, the turnover intentions increase with the group conflict, especially when high group conflict is presented.

Table 4.8 Arrival Scenario I-Base Case

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	100%	0.02	98.8%	0.34	94.7%	0.51	90.4%	0.63
turnover intentions	0%	0.05	3.0%	0.47	10.0%	0.58	16.6%	0.64
Unmet need	976.1	15.32	245.8	12.69	92.0	13.78	2.3	4.37

Table 4.9 Arrival Scenario I-Moderate Group Conflict

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	100%	0.05	97.1%	0.60	89.1%	0.89	82.1%	0.76
turnover intentions	0.1%	0.12	5.6%	0.69	16.6%	0.89	25.2%	0.70
Unmet need	976.3	15.72	247.0	12.6	95.2	12.37	2.3	5.27

Table 4.10 Arrival Scenario I-High Group Conflict

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	99.8%	0.16	90.2%	0.98	72.7%	1.32	59.0%	1.12
turnover intentions	0.7%	0.36	14.1%	1.02	32.7%	1.11	46.0%	0.89
Unmet need	975.3	14.32	246.3	14.22	93.1	11.74	1.48	3.12

As seen in Figure 4.3, for the base case, overall satisfaction remains unchanged for CLs of 0.5 and 1 but drops a little for CL = 1.5 and 2. In comparison, for the scenarios with medium and high conflict among the volunteers, the overall satisfaction starts to drop faster as the CL increases beyond 1. This implies that for a CL of 0.5 to 1, the overall satisfaction percentage stays high even though the conflict level increases. As the CL increases, the mean satisfaction drops faster with increasing levels of conflict.

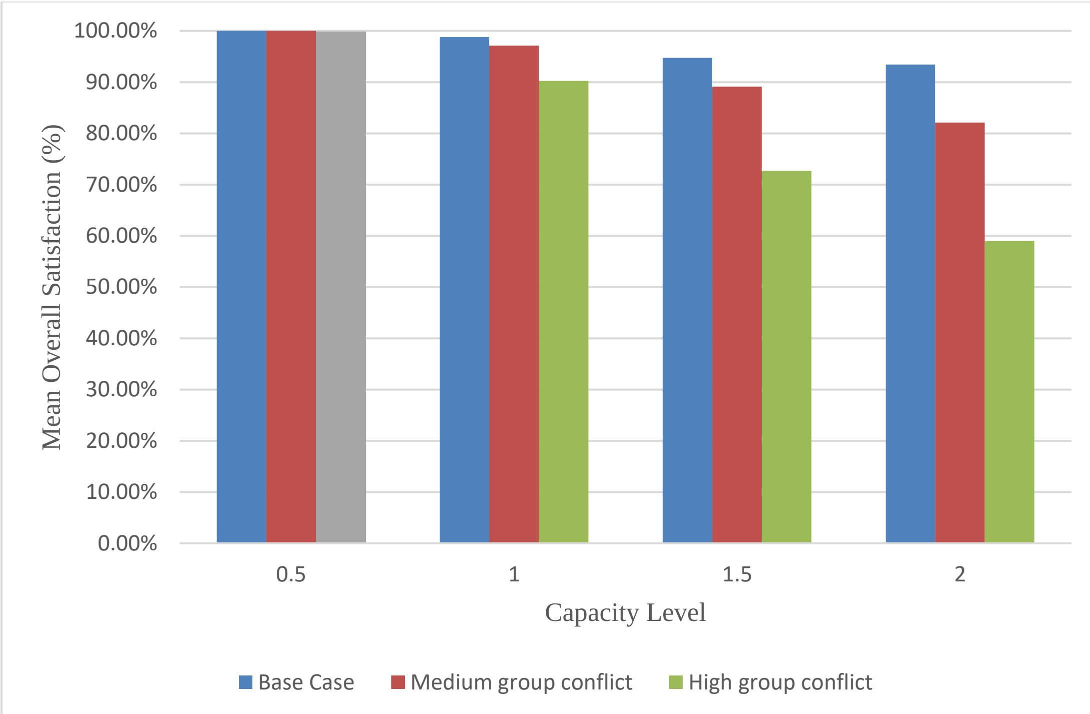

Figure 4.3 Overall Satisfaction across Varying Conflict Levels-Arrival Scenario I

As shown in Figure 4.4, the turnover intentions increase as the CL increases beyond 1. This shows that if there was a surplus of volunteers, their intention to stay would diminish over time as there would be less work for each individual. This becomes more pronounced as we factor in the level of conflict. For medium to high conflict levels, the turnover intentions rise much faster than in the base case scenario.

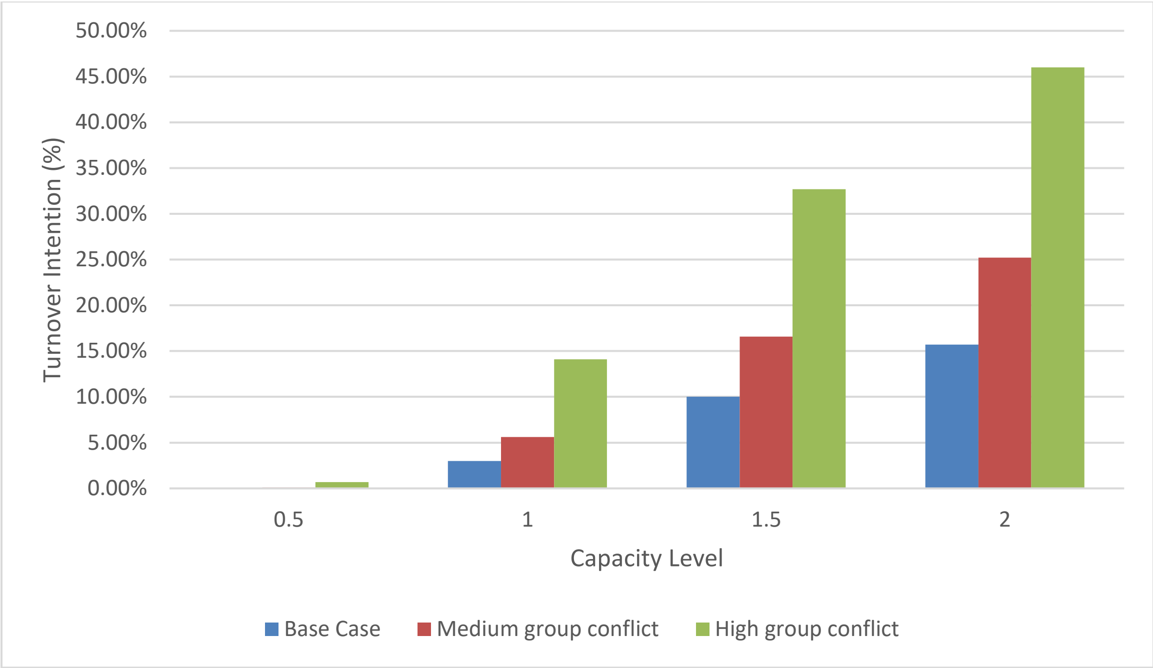

Figure 4.4 Turnover Intention across Varying Conflict Levels-Arrival Scenario I

As the unmet needs value indicates a deficit of volunteers, this value is quite high for CL = 0.5. As we approach a CL of 1, the unmet needs value drops drastically and shows only a small value, indicating a possible need for reserve volunteers. Beyond CL = 1, the unmet needs value drops to 0 (Figure 4.5).

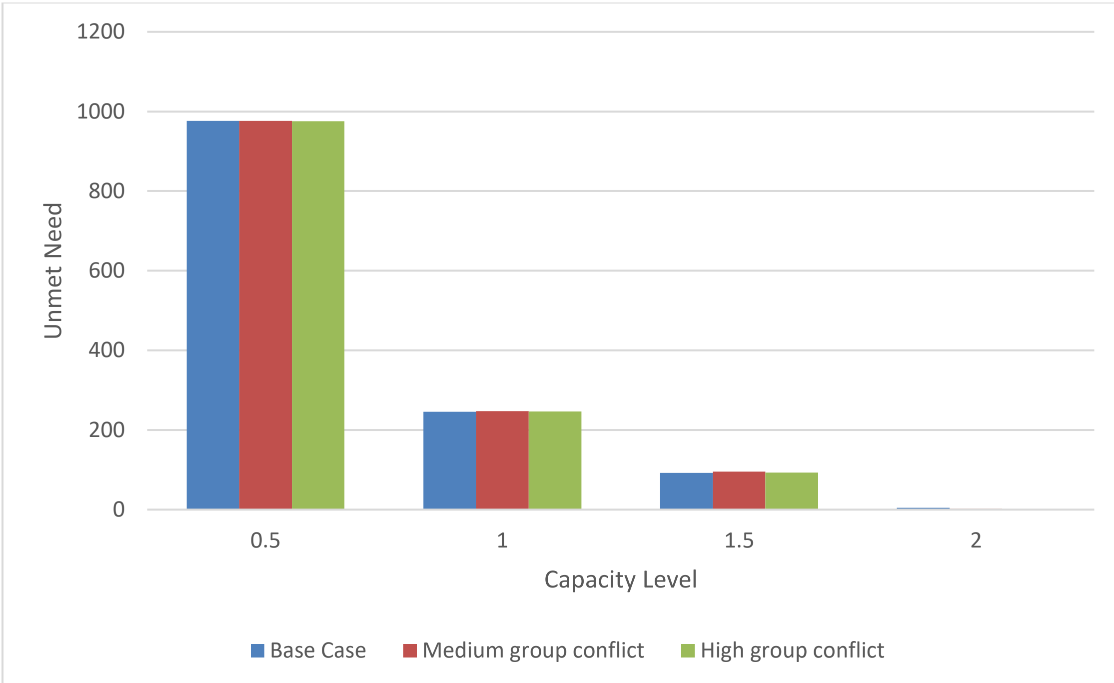

Figure 4.5 Unmet Needs across Varying Conflict Levels-Arrival Scenario I

Tables 4.11, 4.12, and 4.13 show somewhat similar behavior for the overall satisfaction and the turnover intentions. Table 4.11 shows the overall satisfaction and turnover intentions results for Scenario II. The overall satisfaction values are high across all CLs, with a decrease to 93% at the CL of 2, which is a slightly higher overall satisfaction value compared with Scenario I. The turnover intentions started at 1.3% at CL = 0.5, which is slightly higher than the corresponding value from Scenario I. However, the turnover intentions increased at a slower rate (CL = 1, 1.5, and 2) compared with Scenario I. The unmet community needs value is very high at CL = 0.5 and drops to 0 as the CL exceeds 1. In Tables 4.12 and 4.13, we consider cases in which more conflict levels are introduced. Overall satisfaction drops quickly when moderate conflict is introduced and drops drastically when high group conflict is presented. In the same manner, the turnover intentions increase as the group conflict increases from moderate to high.

Table 4.11 Arrival Scenario II-Base Case

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	99.6%	0.14	99.6%	0.11	97.0%	0.42	93.4%	0.88
Turnover intention	1.2%	0.20	1.3%	0.25	9.2%	0.56	15.7%	0.87
Unmet need	1112.3	13.85	80.7	17.15	0.0	0.0	0.0	0.0

Table 4.12 Arrival Scenario II-Medium Group Conflict

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	99.6%	0.13	99.6%	0.12	93.7%	0.62	86.41%	0.99
turnover intentions	1.3%	0.22	1.5%	0.25	13.9%	0.63	23.2%	0.80
Unmet need	1110.4.2	12.26	80.6	20.51	0.00	0.0	0.0	0.0

Table 4.13 Arrival Scenario II-High Group Conflict

	CL =0.5		CL =1		CL =1.5		CL = 2	
	M	SD	M	SD	M	SD	M	SD
Satisfaction	99.5%	0.16	99.4%	0.20	89.9%	1.03	67.8%	1.23
turnover intentions	1.8%	0.25	2.19%	0.53	24.0%	0.92	39.3%	0.88
Unmet need	1110.2	14.99	76.0	21.4	0.00	0.0	0.0	0.0

As shown in Figure 4.6, Scenario II (the base case) shows how the overall satisfaction remains unchanged for CLs of 0.5 and 1 but drops slightly for CLs = 1.5 and 2. In contrast, for the scenarios with medium and high conflict among the volunteers, the overall satisfaction behaves similarly as in Scenario I. It starts to drop faster as the CL increases beyond 1. This also implies that for a CL of 0.5 to 1, the overall satisfaction percentage stays high even though the conflict level increases. As the CL increases, the overall satisfaction drops faster with increasing levels of conflict

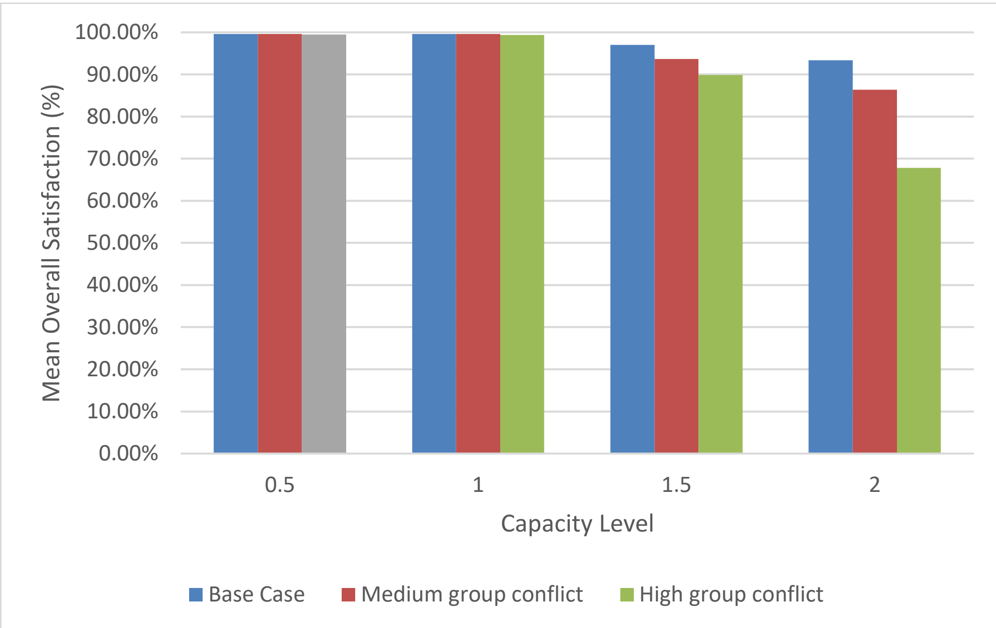

Figure 4.6 Overall Satisfaction across Varying Conflict Levels-Arrival Scenario II

As shown in Figure 4.7, compared with Scenario I, the turnover intentions increase more as the CL increases beyond 1. This shows that if there was a surplus of volunteers, due to their arrival pattern, the volunteers' turnover intentions would tremendously increase over time as there would be less work for each individual. This becomes more pronounced as we factor in the level of conflict. For medium to high conflict levels, the turnover intentions rise much faster than in the base case scenario.

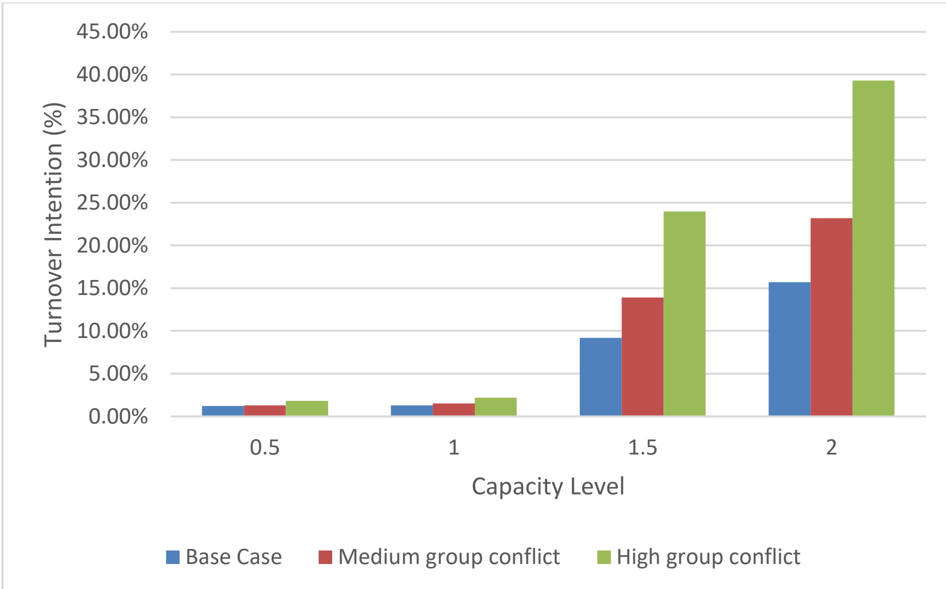

Figure 4.7 Turnover Intention across Varying Conflict Levels-Arrival Scenario II

As the unmet needs value indicates a shortage of volunteers, this value is quite high for CL = 0.5. However, the unmet needs value is less prominent in this Scenario compared with Scenario I because volunteers arrive in large numbers, so they accumulate faster and serve more of the community needs. As we approach a CL of 1.5, the unmet needs value drops drastically and shows only a small value, indicating a possible need for reserve volunteers at CL = 1.5. Beyond CL = 1.5, the unmet needs value drops to 0 (Figure 4.8).

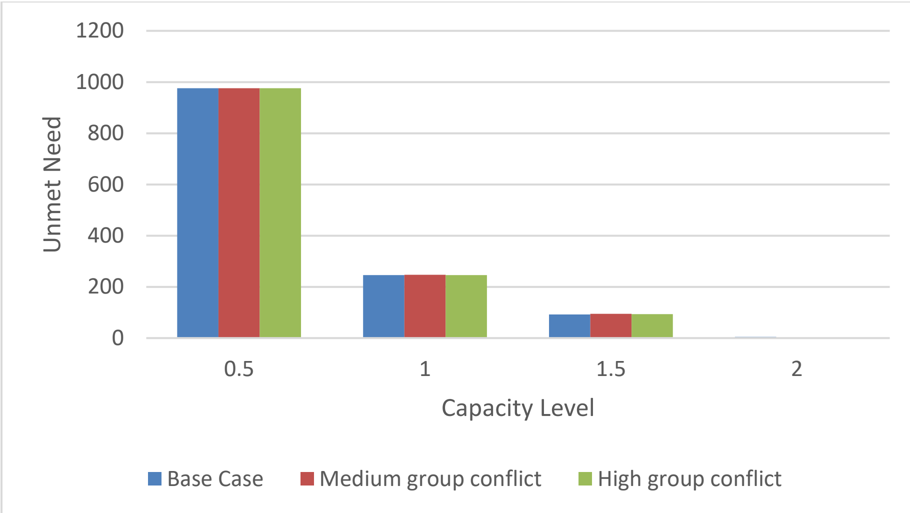

Figure 4.8 Unmet Needs across Varying Conflict Levels-Arrival Scenario II

Discussion and Conclusion

The purpose of this work is to propose and develop a simulation modeling approach to studying the effects of different managerial policies on unmet community needs and disaster volunteers' levels of satisfaction and turnover intentions with an organization during a relief event. We surveyed disaster volunteer managers to explore how they manage volunteers during a relief event to accomplish this purpose. In addition, we used the responses from the survey and the statistical findings from Chapter 3 to develop a simulation model that evaluates the effect of disaster volunteer managers' decision-making on unmet community needs as well as on the satisfaction and turnover intention of disaster volunteers.

Using the information from Chapter 3, we conducted a multiple linear regression on disaster volunteers' overall satisfaction and turnover intention. The results suggest that satisfaction with the work environment has a significant positive relationship with disaster volunteers' overall satisfaction while gender, age, education level, and level of experience did not have an impact. Also, overall satisfaction, satisfaction with the work environment, and the level of experience negatively predict turnover intentions while age, gender, and education level do not have a significant influence.

In addition, using the structural equation model from Chapter 3, we discovered the independent relationships of job fit, workload, and volunteer group with overall satisfaction and turnover intentions. The workload has the highest positive relationship with overall satisfaction followed by the volunteer group and job fit; the highest negative relationship on the turnover intention was the workload followed by the volunteer group and job fit. These findings were used to track disaster volunteer behavior during a relief event.

Regarding the disaster volunteer survey, the summary of the responses provided us with some useful information regarding disaster volunteer information, and how disaster volunteer managers manage volunteers during a relief event. That information was used to build the simulation model.

In the simulation model, we tested managerial decision-making across different values of group conflict levels and capacity levels. Specifically, we considered a scenario where disaster volunteer managers assign a reasonable workload to volunteers rather than a high workload, and if there is increased demand, they will wait for other volunteers to come the following week. In addition, we also considered that each volunteer would have a one-week assignment, and all assignments would be redistributed among current and new volunteer arrivals. The results of this study suggest that only when the number of available volunteers is more than needed does the overall satisfaction increase; the turnover intention decreases due to dissatisfaction with a non-essential workload as well as from group conflict. When the number of volunteers is less than what is needed, disaster volunteers' satisfaction and turnover intentions were not affected even if there is high group conflict due to the positive effect of the workload that offsets the negative impact of the group conflict.

There are some limitations to this work. First, direct communication with disaster volunteer managers in the form of interviews would provide more opportunities to learn about disaster volunteer management. Volunteering in disaster relief efforts could also be an effective, direct way to experience and learn about how volunteers are managed in such situations. Another limitation is that more experimentation and different combinations of scenario are needed to understand how a wider range of variables and parameters influence the performance measures.

There are future directions for this work. The simulation model could be improved for a scenario where a high workload is assigned to volunteers. The simulation model could be expanded to handle multiple tasks and work locations so that more groups can be formed in a way that minimizes the likelihood of conflicts arising. Also, the simulation work could be improved to evaluate not only managerial decision-making but optimize volunteer assignments and workload sharing in a way that would positively impact volunteer behavior while also ensuring that community needs are met as quickly as possible.

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CHAPTER FIVE

CONCLUSION

In this research, we collected online data from disaster volunteers to better understand how disaster volunteer satisfaction and their turnover intentions are predicted by work environment factors. We also collected online data from disaster volunteer managers to learn how they manage their volunteers during relief efforts. We used the collected data to model and evaluate how decision-making affects both disaster volunteer behavior and unmet community needs.

In the initial study, before gathering the online data, we presented the formulation of the VMM with an illustration of the model's objective function, constraints, and assumptions. The goal is to minimize the cost of unfulfilled community needs, volunteer attrition due to mismatched assignments, and volunteer expenses. This model focuses on the loss of volunteers due to assignment preference mismatches.

In the second study, we used an online survey to see how work environment factors explain the level of satisfaction and turnover intention of disaster volunteers. We used CFA and structural equation modeling to test the measurement model and answer the research questions on volunteer behavior. We considered the job fit, training, workload, volunteer group, and supervisor as important factors upon which to test the hypotheses and develop prediction equations. The results propose that the noted work environment factors positively and significantly predict the volunteers' satisfaction and intention to stay and negatively and significantly predict the volunteers' turnover intentions.

In the third study, the main focus was on developing a simulation model. This model should provide a picture of the relation between the volunteers' satisfaction, their turnover intention, and the management decisions of an NGO during a relief event. We developed a realistic relief event and a hybrid simulation model that addresses volunteer task and location assignments, as well as the workload. Furthermore, we presented an evaluation of the effect of management decisions on unmet community needs, as well as volunteer satisfaction and their intention to leave the organization. We considered a situation where volunteer managers do not increase the volunteers' workload. Also, we modeled the assignment decision to allow the redistribution of assignments to current and new volunteers. We tested this decision policy across different group conflict levels and three capacity levels. The results suggest that at high group conflict levels, as the capacity level increases, more volunteers arrive at the affected area and this leads to many volunteers with non-essential tasks, causing their satisfaction to decrease and their turnover intention to increase. We recommend that disaster volunteer managers and NGOs work closely with volunteers to improve the group atmosphere and reduce conflicts. Also, task assignments and workload should be distributed in a way that ensures a fair workload for most of the volunteers.

There are limitations to this research. In the first study, no data were available, so many assumptions were made based on our understanding from the literature and NGO websites. The second study focused on only two organizations to recruit a reasonable number of disaster volunteers for the study. As a result, the findings are not generalizable to other organizations. In the third study, due to the uncertain environment of the disasters and the small sample size of the disaster managers in the survey, we based our assumptions only on what we learned from the disaster volunteer managers' responses.

In future versions of the simulation model, we will consider more testing of managerial decision-making, such as high workload assignments. Also, we will consider how disaster volunteer satisfaction and turnover intentions change in response to negative or positive experiences of their work environment. Additionally, in the future, we will consider not only evaluating the effect of disaster volunteer managers on unmet community needs and volunteer behavior but rather find the optimal decisions that minimize unmet community needs and volunteers' turnover intentions while maximizing their satisfaction with the organization. Lastly, we will seek the cooperation of relief organizations so that we will benefit and learn from experts in the field and gain data from their volunteers.

APPENDICES

Appendix A

Dear Dr. Taaffe and Wahab,

We implemented new exempt review procedures on May 1 (attached) and revised the amendment process for exempt determinations. IRB oversight is no longer necessary for exempt reviews unless one of three conditions in the e-mail message applies.

I reviewed the documents you submitted, and the project continues to meet the criteria for exemption. A formal amendment is not required to implement the changes outlined on the request form, but I made some edits to the informed consent documents since you are requesting the name of the organization on the surveys.

All references to protecting their privacy was removed and risk statement was updated. On the managers' consent document, a statement about identifying the organization was added.

Let me know if you have any questions.

Kind regards,
Nalinee

Nalinee D. Patin, CIP | IRB Administrator

Clemson University

Office of Research Compliance - IRB

Clemson Centre, 391 College Avenue, Suite 406

Clemson, SC 29631

(864) 656-0636 | npatin@clemson.edu

IRB E-mail: irb@clemson.edu (send all new requests to IRB inbox)

Web site: http://www.clemson.edu/research/compliance/irb/

Appendix B

Subject: Re: No'ce of Changes to IRB Review of Exempt Protocols: Effec've May 1, 2017
Date: Thursday, May 4, 2017 at 1:29:27 PM Eastern Daylight Time
From: Nalinee Pa'n
To: INST REVIEW BOARD

From: INST REVIEW BOARD <irb@clemson.edu>
Date: Sunday, April 30, 2017 at 7:26 PM
Subject: No'ce of Changes to IRB Review of Exempt Protocols: Effec've May 1, 2017

Dear Investigators,

Effective May 1, 2017, research protocols that have been determined to meet the criteria for exempt review by the Office of Research Compliance (ORC) or Institutional Review Board (IRB) will no longer be assigned expiration dates.

After the ORC/IRB determines that the research meets at least one of the categories of exemption in accordance with federal regulations 45 CFR 46.101(b), http://media.clemson.edu/research/compliance/irb/exemption-categories.pdf, the investigators will be notified of the determination and no further oversight of the protocol is required except in the following
situations:

1. Substantial changes made to the protocol that could potentially change the review level. Researchers who modify the study purpose, study sample, or research methods and instruments in ways not covered by the exempt categories will need to submit an expedited or full board review application.
2. Occurrence of adverse event or unanticipated problems
3. Change in Principal Investigator (PI)

If there are no changes to the protocol that would require ORC/IRB review, the research team may continue to conduct the study under the initial determination for the duration of the project.

CITI training:
The PI is required to complete the CITI human subjects training course, http://www.clemson.edu/research/compliance/irb/training.html. Other research personnel only involved with exempt studies are recommended to complete the CITI training.

Existing Exempt protocols:
No further oversight is necessary unless one of the conditions above is met (i.e., substantial changes, adverse event/unanticipated problem or new PI).

All research involving human participants must maintain an ethically appropriate standard, which serves to protect the rights and welfare of the participants. This involves obtaining informed consent and maintaining confidentiality of data.

For more information, please refer to our FAQ page,

http://www.clemson.edu/research/compliance/irb/faq.html.
Sincerely,
Office of Research Compliance - IRB
Clemson Centre, 391 College Avenue, Suite 406
Clemson, SC 29631
IRB E-mail: irb@clemson.edu
Web site: http://www.clemson.edu/research/compliance/irb/

Appendix C

Information about Being in a Research Study
Clemson University

Intention to Stay or Quit for Disaster Volunteers during Relief Efforts

Dear Disaster Volunteer,

My name is Abdelwahab Alwahishie, and I am a PhD student in industrial engineering department at Clemson University. I am conducting this research under the supervision of Dr. Kevin Taaffe. We are inviting you to take part in a research study which is part of my doctoral dissertation. The purpose of this research is to determine potential areas of improvement in the volunteer experience during relief efforts.

Your participation in the study is voluntary. Your part in the study will be to complete the following survey. It will take you about 15 minutes to complete. We do not know of any risk or discomfort to you in this research study. We will do everything we can to protect the confidentiality of the information you share with us. Your information will not be shared with the relief organization.

If you have any questions or concerns about this study, please do not hesitate to contact me or Dr. Kevin Taaffe at:

Abdelwahab Alwahishie: (404) 903-2189 or aalwahi@g.clemson.edu
Dr. Kevin Taaffe: (864) 656-0291 or taaffe@clemson.edu

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) irb@clemson.edu or 866-297-3071.

Clicking on the "agree" button indicates that:

- You have read the above information
- You voluntarily agree to participate
- You are at least 18 years of age

Disaster volunteer survey

I am satisfied with:

	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly Agree
For quality assurance purposes, please select 'strongly disagree'	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The fit of the job assignment to my preferences	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Volunteers in my group	⊙	⊙	⊙	⊙	⊙	⊙	⊙
My assigned workload	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The fit of the job assignment to my skill	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The onsite training	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Pre-service training	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The fit of the job assignment to my schedule	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The instructions on the job	⊙	⊙	⊙	⊙	⊙	⊙	⊙
My supervisor	⊙	⊙	⊙	⊙	⊙	⊙	⊙

	Very unlikely	Unlikely	Somewhat unlikely	Neutral	Somewhat likely	Likely	Very likely
How likely will you volunteer with this organization for the next year	⊙	⊙	⊙	⊙	⊙	⊙	⊙
How likely will you volunteer with this organization for the next three years	⊙	⊙	⊙	⊙	⊙	⊙	⊙

Please indicate to what extent you disagree or agree with the following statements:							
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly Agree
My workload is reasonable	⊙	⊙	⊙	⊙	⊙	⊙	⊙
My workload is about right	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I enjoy working with my supervisor	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I have a good relationship with my supervisor	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I have a good relationship with the volunteers in my group	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I enjoy working with the volunteers in my group	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Overall, I am satisfied with the volunteer experience at this organization	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I intend to quit volunteering with this organization in the next year	⊙	⊙	⊙	⊙	⊙	⊙	⊙
I intend to quit volunteering with this organization in the next three years	⊙	⊙	⊙	⊙	⊙	⊙	⊙

How old are you?	
⊙	18-24 years old
⊙	25-34 years old
⊙	35-44 years old
⊙	45-54 years old
⊙	55-64 years old
⊙	65-74 years old
⊙	75 years and over

What is your sex	
⊙	Male
⊙	Female

What is the highest level of school you have completed or the highest degree you have received?	
⊙	Less than high school degree
⊙	High school graduate (high school diploma or equivalent including GED)
⊙	Some college but no degree
⊙	Associate degree in college (2-year)
⊙	Bachelor's degree in college (4-year)
⊙	Master's degree
⊙	Doctoral degree
⊙	Professional degree (JD, MD)

How long have you been volunteering with this organization?	
⊙	6 months or less
⊙	7 to 11 months
⊙	1 to 2 years
⊙	3 to 5 years
⊙	6 to 10 years
⊙	More than 10 years

Appendix D

Information about Being in a Research Study

Clemson University

Disaster Volunteer Management during Relief Efforts

Dear Disaster Volunteer Manager,

My name is Abdelwahab Alwahishie, and I am a PhD student in industrial engineering department at Clemson University under the supervision of Dr. Kevin Taaffe. We are inviting you to take part in a research study which is part of my doctoral dissertation. The purpose of this research is to improve volunteers' effectiveness and satisfaction during relief efforts.

Your participation in the study is voluntary. Your part in the study will be to complete the following survey. It will take you about 20 minutes to complete. We do not know of any risk or discomfort to you in this research study. The results of this study will be used in order to determine the potential improvement in volunteer management practices that lead to accomplishing the most good for population in need and a reduction in volunteer dissatisfaction and intention to quit. With your permission, the organization may be identified in the final report.

If you have any questions or concerns about this study, please do not hesitate to contact me or Dr. Kevin Taaffe at:

Abdelwahab Alwahishie:	(404) 903-2189 or aalwahi@g.clemson.edu
Dr. Kevin Taaffe:	(864) 656-0291 or taaffe@clemson.edu

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at irb@clemson.edu or 866-297-3071.

Disaster volunteer manager survey

What is the organization that you have the most recent disaster volunteering management experience with?	
⊙	Red Cross
⊙	Habitat for humanity
⊙	Other
⊙	None

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
How often do you have more disaster volunteers than needed in a given week?	⊙	⊙	⊙	⊙	⊙	⊙	⊙

How do you manage the extra disaster volunteers?

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
Provide them with non-essential jobs	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Redistribute workload across all Volunteers	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Turn them a way	⊙	⊙	⊙	⊙	⊙	⊙	⊙

(Optional) If there is any additional decisions about how to manage the extra disaster volunteers, please enter them below.

When you have extra disaster volunteers than you need in a given week, the selection criterion for volunteers to perform the available jobs is based on:

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
Volunteer preferences	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Volunteer skill level	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Volunteers are selected randomly to perform jobs	⊙	⊙	⊙	⊙	⊙	⊙	⊙

(Optional) If there is any additional selection criterion for performing the jobs when there are extra disaster volunteers, please enter them below.

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
How often do you have less disaster volunteers than needed in a given week?	⊙	⊙	⊙	⊙	⊙	⊙	⊙

How do you manage the shortage of disaster volunteers?							
	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
Reach out to other organization to get volunteers	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Do the regular workload with available volunteers and wait for more volunteers to come	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Put more workload on available volunteers	⊙	⊙	⊙	⊙	⊙	⊙	⊙

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
If there is a shortage of volunteers at one site and extra volunteers at other sites, how often do you move volunteers between sites to complete the relief effort?	⊙	⊙	⊙	⊙	⊙	⊙	⊙

(Optional) If there are any additional decisions about managing the shortage of disaster volunteers, please enter them below.

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
When you reach to other organizations to get volunteers, how often that you get enough disaster volunteers?	⊙	⊙	⊙	⊙	⊙	⊙	⊙

When new volunteers arrive while other volunteers are already working, how do you manage assignments?

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
Existing volunteers continue to work on their assigned jobs, and the new volunteers get assigned to the available work opportunities.	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Redistribute the existing and the new volunteers to the available jobs.	⊙	⊙	⊙	⊙	⊙	⊙	⊙

From your experience with disaster volunteers at your organization, please answer the following questions:

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
What is the percentage of disaster volunteers who quit volunteering with this organization in the last three years?	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙
What is the percentage of disaster volunteers who were dissatisfied with their volunteering experience in the last three years?	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙

How often does each of the following three volunteer arrival patterns occur?							
	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
The number of arriving volunteers is large at the beginning of the disaster relief event, and gradually decreases until the end of the disaster relief event.	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The number of arriving volunteers is small at the beginning of the disaster relief event, and gradually increases until the end of the disaster relief event.	⊙	⊙	⊙	⊙	⊙	⊙	⊙
The number of arriving volunteers is small at the beginning of the disaster relief event, and gradually increases to a peak until the middle of the disaster relief event, then decreases again until the end of the disaster relief event.	⊙	⊙	⊙	⊙	⊙	⊙	⊙

(Optional) Please provide any more description of how the number of arrival volunteers changes from week to week during the disaster relief event.

During a relief event, how predictable is the number of volunteers arriving per week?	
⊙	Very unpredictable
⊙	Unpredictable
⊙	Somewhat unpredictable
⊙	Neutral
⊙	Somewhat predictable
⊙	Predictable
⊙	Very predictable

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
How often do volunteers sign up for a specific time commitment? (e.g. four weeks)	⊙	⊙	⊙	⊙	⊙	⊙	⊙

	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
How often do volunteers leave before they complete their time commitment?)	⊙	⊙	⊙	⊙	⊙	⊙	⊙

From your experience, how often do these reasons lead to conflict among volunteers?							
	Never	Very rarely	Rarely	Sometimes	Frequently	Very frequently	Always
Difference in age	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Difference in skill level	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Difference in education Level	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Difference in experience	⊙	⊙	⊙	⊙	⊙	⊙	⊙

(Optional) Is there any other reasons lead to conflict among volunteers? If so, please enter them below.

How long do volunteers typically spend in on-site training to gain construction skill?

Please specify hours, days or weeks and enter a number in the box.

Hours	Days	Weeks

Provide a typical percentage of disaster volunteers who have skills: (Total should equal 100)											
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Disaster volunteers who are skilled at few jobs	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙
Disaster volunteers who are skilled at many jobs	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙

What is your sex	
⊙	Male
⊙	Female

How long have you been volunteering with this organization?	
⊙	6 months or less
⊙	7 to 11 months
⊙	1 to 2 years
⊙	3 to 5 years
⊙	6 to 10 years
⊙	More than 10 years