DEVELOPING A DECISION SUPPORT SYSTEM FOR CREATING POST DISASTER TEMPORARY HOUSING

by

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To My Lovely Parents and the family of all Iranian students who have been stripped the right to see their children through no fault of their own

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ABSTRACT

Post-disaster temporary housing has been a significant challenge for the emergency management group and industries for many years. According to reports by the Department of Homeland Security (DHS), housing in states and territories is ranked as the second to last proficient in 32 core capabilities for preparedness. The number of temporary housing required in a geographic area is influenced by a variety of factors, including social issues, financial concerns, labor workforce availability, and climate conditions. Acknowledging and creating a balance between these interconnected needs is considered as one of the main challenges that need to be addressed. Post-disaster temporary housing is a multi-objective process, thus reaching the optimized model relies on how different elements and objectives interact, sometimes even conflicting, with each other. This makes decision making in post-disaster construction more restricted and challenging, which has caused ineffective management in post-disaster housing reconstruction.

Few researches have studied the use of Artificial Intelligence modeling to reduce the time and cost of post-disaster sheltering. However, there is a lack of research and knowledge gap regarding the selection and the magnitude of effect of different factors of the most optimized type of Temporary Housing Units (THU) in a post-disaster event.

The proposed framework in this research uses supervised machine learing to maximize certain design aspects of and minimize some of the difficulties to better support creating temporary houses in post-disaster situations. The outcome in this study is the classification type of the THU, more particularly, classifying THUs based on whether they are built on-site or off-site. In order to collect primary data for creating the model and evaluating the magnitude of effect for each factor in the process, a set of surveys were distributed between the key players and policymakers who play a role in providing temporary housing to people affected by natural disasters in the United States. The outcome of this framework benefits from tacit knowledge of the experts in the field to show the challenges and issues in the subject. The result of this study is a data-based multi-objective decision-making tool for selecting the THU type. Using this tool, policymakers who are in charge of selecting and allocating post-disaster accommodations can select the THU type most responsive to the local needs and characteristics of the affected people in each natural disaster.

CHAPTER 1. INTRODUCTION

Chapter 1 provides an overview of this research study. This chapter provides the scope, purpose, research questions, assumptions, limitations, and delimitations of the project.

1.1 Scope

According to the International Displacement Monitoring Centre (IDMC), 14 million people annually lose their homes due to natural disasters (Danan, Gerland, Pelletier, & Cohen, 2015) worldwide. Providing affected families with temporary shelters is considered a top priority (Leefeldt, 2017). Creating post-disaster temporary shelters appropriate to the specific community is considered an arduous task as it contains lots of uncertainty and complexities (Gotham & Cheek, 2017; Hidayat & Egbu, 2010; Leefeldt, 2017). According to reports by the Department of Homeland Security (DHS), housing in states and territories is ranked as the second to last proficient in 32 core capabilities for preparedness (Department of Homeland Security, 2018). Furthermore, this situation has been exacerbated in recent years and continues to worsen due to the density growth in cities and environmental degradation. For example, soil disintegration and an increase in the frequency of natural disasters (Banholzer, Kossin, & Donner, 2014; Hayles, 2010; Susman, O'Keefe, & Wisner, 2019). It affects the region, and the scope widens to adjacent cities and states as people would seek temporary housing in those places.

In addition, the scarcity of data and factors are other problems that policymakers face while providing temporary housing (Jachimowicz, 2014). Lack of data and no guidance on the influence of temporary housing factors will result in housing dissatisfaction.

This research aims to develop a framework that can assist in creating quality temporary houses in the post-disaster situation and help them with the decision-making process by optimizing different aspects of the process. This tool's users will be the stakeholders and contractors who provide temporary housing in the managerial position for the affected people. The framework would help the policymakers select the most suitable and appropriate THU type based on the importance of factors.

1.2 Significance

Temporary houses are the link between emergency sheltering, which should not be more than a week, to permanent housing, which can take years to be built (Quarantelli, 1991). Therefore, temporary houses need to meet a broad range of standards while settling in a short time. However, it should not be as sophisticated as a permanent house to let the people move to their permanent houses when the time comes. A majority of the disaster victims who will seek temporary housing will have no control in the form of housing provided to them and must accept any assistance is offered to them. (McCarthy, 2008). Thus, any consideration must be made on the stakeholder side to ensure that the housing fits the user. These criteria make temporary housing unique and essential in the whole recovery process.

Besides, in the last century, two major factors have contributed to the importance of temporary sheltering: 1) the increase of natural disasters both in destruction and occurrence (Banholzer et al., 2014; Hayles, 2010; Susman et al., 2019), and the frequency of natural disasters are increasing in a way that they are becoming more of a norm than a rare occurrence. 2) As the population increase, more people are now living in urban communities. With the population growth in the modern time, people now tend to live in cities more than ever, especially the coastal lines where cities are experiencing a high density and population increase (Sweet et al., 2017).

1.3 Research Question

The specific research fundamental questions the researcher intends to explore are:

1. What are the factors that contribute to the temporary housing construction process that affect all stakeholders?
2. What is the weight and magnitude effect of each factor in the process?
3. What is the effect of multi-objective design in temporary housing design?

1.4 Statement of Purpose

The purpose of this study is to create a decision-making framework in order to facilitate the selection process of the most proper, applicable, and effective type of post-disaster temporary houses for each occurrence. This process is able to be achieved by optimizing the factors that affect building the temporary houses. Preliminary research indicates that a systemized, constructed evaluation strategy can enhance the total process. Therefore, the hypothesis is that using a combination of artificial intelligence and a multi-criteria decision-making model via deterministic data can support the decision-making system for creating temporary structures in post-disaster situations.

1.5 Assumptions

Assumptions of this research are identified as the following:

1. The survey and interview instruments are appropriately designed to obtain straight, succint, and unambiguous responses.
2. Respondents will answer the online survey and interview questions truthfully and unbiasedly.
3. The sample for the online survey is a significant representation of the United States' post-disaster temporary housing projects; and
4. A reasonable rate of response will be achieved.

1.6 Limitations

Limitations of this research are:

1. The validation and the weights of the factors that affect the decision making for post-disaster temporary housing depend on the experts' perceptions from FEMA and post-disaster contractors;
2. The study will be limited by the FEMA and post-disaster contractors’ willingness to cooperate;
3. The population of the post-disaster contractors is limited; and
4. The study's generalizability to other geographical places will depend on the factors validated by the experts to be adopted in the study.

1.7 Delimitations

The following delimitations are identified as follows:

1. This research only covers temporary housing and does not cover emergency response or permanent housing;
2. The research will be conducted with agencies and contractors from firms and companies within the United States; and
3. The study only focuses on natural post-disaster housing and does not cover war attacks, terrorism, etc.

1.8 Definitions

Below is a list of definitions that are deemed supportive of this research:

1. Disaster: A significant disruption of a community's or society's functioning that results in widespread human, material, economic, or environmental losses that exceed the affected community's or society's capacity to cope using its resources (FEMA, 1990).
2. Temporary House: "A habitable covered living space and a secure, healthy living environment, with privacy and dignity, to those within it, during the period between a conflict or natural disaster and the achievement of a durable shelter solution" (Corsellis & Vitale, 2005, p. 11).
3. Environmental Impact: Any change to the environment, whether adverse or beneficial, wholly or partially resulting from an organization's activities, products, or services (Bai & Bai, 2014).
4. Multi-Criteria Model: A model which "deals with decisions involving the choice of a best alternative from several potential candidates in a decision, subject to several criteria or attribute that may be concrete or vague" (Pavan & Todeschini, 2009, p. 591).

1.9 Summary

The background, significance, purpose, research questions, scope, and definitions of the study were all covered in this chapter. The following section contains a summary of applicable literature from the following areas: post-disaster housing building strategy, post-disaster construction, temporary housing construction criteria, decision making, and multi-objective optimization tools. The condition assessment factors are outlined in Chapter 2. The developed condition assessment model is specified based on these factors.

CHAPTER 2. LITERATURE REVIEW

A portion of this chapter is pending publication in the Journal of Emergency Management.
In this section, the author first explains the review's methodology by identifying and reviewing key research literature relevant to the problem. Next, the researcher discusses the topics pertinent to the research and the lack of available literature. This literature review's related topics are post-disaster housing building strategy, post-disaster construction, temporary housing construction criteria, and multi-criteria decision-making tools.

2.1 Methodology of the review

The author uses qualitative research approaches in the literature review to synthesize qualitative-based works. For this research, the researcher used the “Academic Search Premier,” “Engineering Village”, and “ProQuest Technology Collection” as a database to conduct this study, with the range of the last twenty years (1999 – 2019). The search included high-ranked peer-reviewed journals, conference proceedings, theses, and dissertations. In addition, official reports from Red Cross, FEMA, and HUD were used as part of the data sources. Figure 2.1 shows the relationship of the key concepts in the literature research.

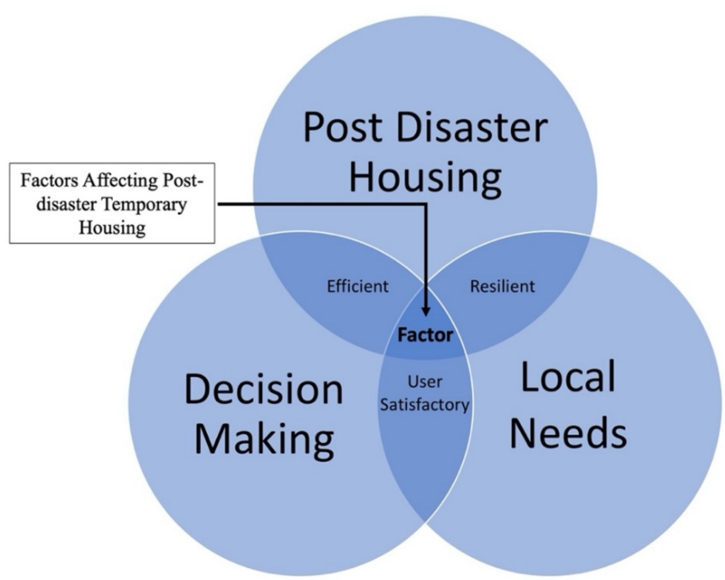


Figure 2.1 Relationship of Key Concepts

The first step is to find out the general factors that can lead to successful temporary housing. It is worth noting that the researchers did not consider war, terrorist attacks, and human-made catastrophes such as nuclear meltdown as a scope of this project. It is only for post-natural disaster housing. It also does not cover sheltering and temporary housing for homeless people or refugees.

2.2 Post Disaster Housing Building Strategy

When a disaster occurs, the first thing is to estimate the number of affected people based on the research's magnitude (Fiedrich, Gehbauer, & Rickers, 2000). Multiple agencies collect shelter resident data. However, there is no robust data collection method or data sharing between agencies (FEMA, 2018). When the magnitude of the disaster is high and the number of people affected in the area is extraordinary, simple relocation to hotels/ motels is not enough (Kulkarni et al., 2008). In these situations, the process of finding alternative housing is considered daunting and arduous. Therefore, after assessing the situation, different organizations on the local, state, and federal scale create the “joint field office” to coordinate national resources between the affected people. If deemed necessary, the office will allocate temporary housing via direct assistance to the people affected (McCarthy, 2012). Housing and sheltering after a disaster is thought to be a cyclic mechanism involving a variety of activities. Most, if not all, of these topics are interconnected and can have an effect on one another's activities and development. This connection and relationship between different tasks becomes more complicated as the population grows and cities develop and become denser. (Afkhamiaghda, Elwakil, & Afsari, 2020). Previous research (Afkhamiaghda, Afsari, Elwakil, & Rapp, 2019) has shown how mapping the post-disaster process will help users make better decisions by allowing them to see all the connections and causes between work tasks.

2.3 Post-Disaster Construction

More than for conventional construction projects, post-disaster construction deals with issues such as time constraints (Karaoğlan & Alaçam, 2019; Rapp, 2011), price fluctuation and inflations (Chang, Wilkinson, Seville, & Potangaroa, 2010), debris and waste management (Yip, 2000) , lack of coordination among agencies, infrastructure breakdown (Bilau, Witt, & Lill, 2017), and resource availability (Chang, Wilkinson, Potangaroa, & Seville, 2011; FEMA, 2009). This makes the temporary housing in post-disaster more restricted and challenging. These houses are “temporary” and are only meant for a specific short period that needs to be considered. Creating transitional houses requires a significant amount of diligence and dexterity as they need to meet the complicated and broad range of affected people’s needs (Dai et al., 2009) in a challenging type of environment (Chang et al., 2010). Building based on people needs and meeting their desires is considered as the top priority and core idea in this kind of construction. This is a highly subjective factor that varies depending on a variety of subjects such as the disaster's severity and type (FEMA, 2009; Platt, 2018) site position, logistics, and the community characteristics such as culture, urban density, population, and the province’s climate situation (Ford, Ahn, & Choi, 2014).

2.4 Temporary Housing Construction Criteria

Different Researchers (Bashawri, Garrity, & Moodley, 2014; Nath, Shannon, Kabali, & Oremus, 2017) have created a review of factors that affect the temporary housing process. However, there are still some factors missing in these studies. In previous research (Afkhamiaghda et al., 2020), the researchers have systematically categorized all the factors that affect post-disaster temporary housing, which is shown in Figure 2.2. In the following section, this study investigates each of the selection criteria for the temporary housing type in more detail.

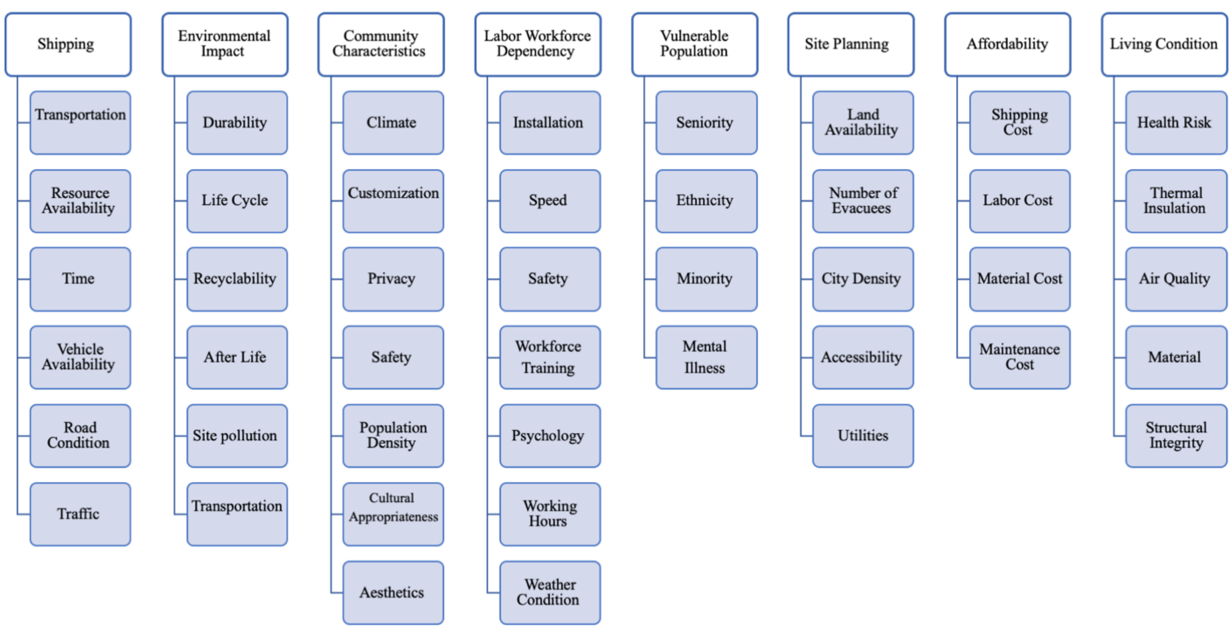


Figure 2.2 Factors Affecting the Temporary Housing Process

2.4.1 Shipping

Post-disaster temporary housing construction can be categorized into two major groups. The first is offsite construction, where most of all, the construction process is done in an indoor factory environment, away from the actual site, and then shipped to the site for assembling (Ford et al., 2014). The second group is onsite construction or the traditional "stick" method, where the raw materials are shipped to the site, and temporary houses are built by labor on site. According to many researchers (Hui Ling, Tan, & Saggaff, 2019; Lopez & Froese, 2016), this criterion can be recapped as the type of the transportation system and the number of shipments needed for creating the temporary houses. Another issue with the shipping process is the late delivery, which can delay the whole temporary housing process.

While some researchers such as (Abulnour, 2014) believe that the best strategy in order to have fast sheltering is to use onsite materials in the event of a natural disaster, many local material suppliers might be damaged or unable to function in such circumstances (Bilau, Witt, & Lill, 2015; Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2014). Therefore, it is required in many scenarios to import the commodities needed for creating shelters for the region. In using off-site temporary housings, this factor will depend on factors such as the distance of the manufactory, vehicle, driver availability, and fuel price (Escamilla & Habert, 2015). Offsite accommodations are more dependent on transportation. Therefore, transportation systems such as roads, airfields, and rails and how much they have been damaged play a vital role (Chang et al., 2010). As the scope of a natural disaster increases, the need for reconstruction grows exponentially, leading to high demand for construction materials and labor in the market (Olsen & Porter, 2013). In addition, transporting these units needs careful planning and specific cargo and trucks. Blocked or damaged routes of travel more restrict the larger assembled modules, and the vehicles and trailers that can move these larger factory-built assemblies are fewer in number (Hui & Ming, 2009). The vehicles and trailers that can move the larger factory-built assemblies are fewer in number. Therefore, transportation can be considered as one of the elements determining the cost of the units. Based on the magnitude of the disaster and the amount of destruction, the access to the site might be compromised and, therefore, not be easily reached (Holguín-Veras et al., 2012; Cho et al., 2001; Seville and Metcalfe, 2005; Litman, 2006; Orabi et al., 2009). In addition, long lines of traffic are expected as many responses as possible and aid vehicles will drive to the affected region (Haghani & Afshar, 2009).

2.4.2 Environmental Impact

Debris and waste management are critical issues in post-disaster situations as a considerable amount of building waste is generated in a short period. Like any other construction task, creating temporary houses can generate a considerable amount of material waste, mostly if it is built on-site and not in a factory and shipped to the site. In addition to material waste, as mentioned previously, resource availability is another issue that the contractors deal with in making post-disaster housing. Suppose the stakeholders choose to use non-local materials. In that case, it is imperative to consider the weight and size of the material and the number of trips needed for bringing the materials (Davis et al., 2019).

Unlike typical construction projects, temporary houses are only meant for a specific short period. Therefore, the life cycle of units after their intended use is of vital importance. While these accommodations are initially created to accommodate between 5 and 24 months, people might end up living in them even up to five years (Atmaca, A., & Atmaca, N. 2016). This gap in the intended timeframe and actual timeframe of the usage can lead to numerous maintenance issues; thus, some researchers such as Song et al. (2016) use lifetime performance as a criterion for evaluating temporary houses.

Constructing a temporary house also has many indirect consequences of environmental impacts, such as greenhouse emissions and the process's energy consumption. Dong et al. (2018) discuss that prefabricated and modular buildings create a considerable amount of pollution in this regard compared to traditional houses. Many researchers (Escamilla & Habert, 2015; Sener & Altun, 2009; Torus & Şener, 2015) discussed how the environmental impact could be measured based on the criteria such as the amount of material waste, noise, and dust pollution generated during the shelter construction.

The afterlife phase of the project is another part of the environmental impact. Prefabricate kits have more degrees of freedom in terms of usage after the disaster. Félix et al. (2013) discuss that they can either be dismantled, reused, sold, demolished, or purchased by occupants for long-term use. However, in terms of traditional onsite houses, this is not the case, many researchers such as Arslan (2007) discuss that it is ideal to reuse salvaged materials from affected houses for constructing new temporary lodgings, which not only help with the debris and waste management of the region, but it can reduce the overall cost of the units noticeably. However, reusing the salvaged materials requires a strict and thorough evaluation and inspection of potentially hazardous substances in the old debris (The United States Environmental Protection Agency, 2004). Materials excavated from flooded areas should go through additional screening to be contaminated from the stagnant water (American Industrial Hygiene Association, 2017). This inspection process needs experts in the field with adequate equipment, making the process costly and adding to its first-proposed time frame. Increasing the lifecycle of the temporary houses not only protracts the overall time of the project, but it also increases the cost significantly (IFRC, 2013).

2.4.3 Community Characteristics

Ginige and Amaratunga (2011) define community as "individuals and groups sharing a natural and built environment that is vulnerable to hazards. In other words, the community is the general public; the users and occupants of the built environment and the beneficiaries of post-disaster reconstruction “(Ginige & Amaratunga, 2011, p. 25). The temporary house users are the affected community's people; therefore, designing these spaces germane to their characteristics is essential. Creating accommodations that ignore the cultural characteristics and the lifestyle of the specific region can bring dissatisfaction to the local users (Dikmen & Elias-Ozkan, 2016). As Bashawri et al. (2014) have discussed, each region and community should have its design style and form for a building based on the region's specific culture and is responsive to that area's climate. When local authorities perform the design and building process compared to the federal government, it better reflects the community's needs and cultures (Windle, Quraishi, & Goentzel, 2019). Kamali and Hewage (2017) have demonstrated sustainable performance indicators in their research. They define elements such as user acceptance and satisfaction of the temporary houses and the building's aesthetic and beauty as social criteria. These criteria are not static but are susceptible to change based on location, time, and generations (Peacock, Dash, & Zhang, 2007).

Climate conditions, population density, and urban patterns are essential for each community when creating temporary houses. As the population grows, the number of people living in cities increases, and therefore, high rise and multi-story buildings become more prevalent (Ford et al., 2014; Murray, 2015). As time progresses, the social formation of families and households changes; as National Research Council (2011) states in their report, changes in the family configuration and immigration, age distribution, and people's expectations have drastically changed the traditional household formation and social patterns. These rapid and spikes in social patterns lead to a broad spectrum of needs, hence the urge to build numerous modules and options which fit all these needs and local issues (Félix, Branco, & Feio, 2013).

Unlike other factors discusses earlier, community characteristics are considered a subjective factor that cannot be measured using conventional systems. The community can apply the cultural needs, user acceptance, and satisfaction to the region by participating in the temporary housing process. Many researchers (Francis, Wilkinson, Mannakkara, & Chang-Richards, 2018; Opdyke, Javernick-Will, & Koschmann, 2018) have accentuated the importance of community participation towards sustainable development of the region. As the National Disaster Housing Strategy (2016) have issued in their report, in order to reach a sustainable recovery, community and individuals need to be supported. Despite its importance, an issue has not been addressed adequately in current post-disaster temporary housing practices (Ingram, Franco, Rio, & Khazai, 2006). The "Community Characteristic" measure needs to consider climate, culture, and the vulnerable group of the inhabitants as well as the regions' density and population (Bashawri et al., 2014; Kamali & Hewage, 2017; Rufat, Tate, Burton, & Maroof, 2015; Torus & Şener, 2015).

2.4.4 Labor Force Dependency

Labor forces on site are considered an integral part of the temporary housing construction process. Recruiting skilled labor in an affected area in a short amount of time can be challenging as a large-scale of construction needs to be done in a short period with a limited amount of skilled labor (Gunawardena, Tuan, Mendis, Aye, & Crawford, 2014; Le Masurier, Rotimi, & Wilkinson, 2006). Contractors can field a team of expert trainers to impart essential construction technical skills and knowledge to create temporary houses for local people. This can reduce overall housing reconstruction times by generating higher productivity with better work quality (Bilau et al., 2015).

The utilization of local knowledge and labor can create microeconomies to aid the recovery process (Zhang et al., 2014).

While manufactured homes are the most prevalent type of temporary housing in developed countries such as the United States, the most underdeveloped countries still use traditional on-site temporary housing in the event of a disaster. Using the labor workforce in post-disaster reconstruction is considered a challenging factor. On one side, researchers such as Murray (2015) have addressed how the workforce and people from the community participating in the construction process are useful. However, this brings a group of experts and novice to a specific kind of job site, which makes the process vulnerable to three kinds of issue:

a- Human Errors:

Human errors are an inevitable part of workforce dependency in the post-disaster situation due to extreme conditions (Abulnour, 2014; Rapp, 2011). Different variables such as lack of skill, working conditions, weather conditions, lack of coordination between different groups, and time limitation involved affecting the labor productivity in construction (Bilau, Witt, & Lill, 2018; Dai, Goodrum, & Maloney, 2007; Drury, Yanco, Howell, Minten, & Casper, 2006). Depending on the scale of the disaster and the affected region's population, the number of temporary houses assigned to be built at any location will vary. Because of this, contractors typically have numerous construction teams working simultaneously in order to save time.

b- Safety:

In the condition of on-site temporary housing, structures are assembled outdoors, making the labors install and construct them vulnerable to weather conditions. Excessive cold, extreme heat, wind velocity, air quality, noise, and humidity are some of the factors that degrade labor performance (Leung et al., 2010). Both cold and hot temperatures can be dangerous for the workers if they need to work outside for an extended time (Ibbs & Sun, 2017). Staying in an outdoor environment for an extended period in wind chill temperatures can lead to fatigue, hypothermia, frostbites, and even death. Similar precautions apply for hot temperature conditions, where employers need to train workers and provide shades and supplies such as water bottles and monitor the workers' wellbeing.

Centers for Disease Control and Prevention (CDC) has issued a safety checklist to perform cleanup and reconstruction in the disaster zone. This checklist contains numerous safety topics: general safety, electrical safety, preventing and treating illness and diseases, as well as cleaning up after an emergency (Centers for Disease Control and Prevention, 2018). Bilau et al. (2015) mentioned labor training as a work process that needs to be performed to use the labor workforce. This training is not limited to teaching the workforce to build but also covers a broad range of safety topics such as chemical and biohazard, physical hazards, and equipment hazard training (Grosskopf, 2010). Therefore, the managers need to invest in time and cost to ensure that the construction team has proper safety training before starting the process.

A post-disaster area can be considered a dangerous place for the clean-up and reconstruction crew. Often, many structures have fallen, and the structural integrity of those remaining is most likely compromised. Therefore, the risk of people falling from heights or part of a structure collapsing on them can be high (Rapp, 2011). Hot electrical power lines are considered a major hazard and deadly around water as any contact can lead to a fatal electric shock (Centers for Disease Control and Prevention, 2017). Broken water and gas pipes are another typical result after such disasters. Therefore, anyone working in this situation must take extreme caution (American Industrial Hygiene Association, 2017). Stagnant water can be a source of many infectious diseases, as well as many respiratory health issues. Even if the source is potable, all water that has flowed over open ground should be treated as blackwater as it might be combined with raw sewage. In these situations, people on the site must wear proper equipment such as protective gloves and goggles, masks, water-resistant uniforms. (Grosskopf, 2010).

c- Speed:

In a construction project, the project manager schedules the timeline based on the project's scale and the deadlines. While the number of crews and workers in the site might vary, the schedule does typically not exceed 8 hours per day, five days a week. However, in post-disaster situations, conditions are very different. Speed is crucial in these scenarios as the victims need to be secured in temporary houses as soon as possible. Although time is critical, the quality of these temporary units also matters. The keen demand for “more, better, faster” production intensifies. Part of the solution is working more hours per day—perhaps extending the effort to twelve hours a day, seven days a week (Rapp, 2011). From before, unlike a regular construction project, the team working in a post-disaster situation maybe a medley of labor, hired by contractors or comprised of volunteers, the latter of whom commonly lack required expertise. The stress and pressure of finishing the work in a limited time in extreme conditions and shortage of skilled labor are considered factors that can cause fatigue and ineffectiveness in the long term in the working personnel and laborers (Berkowitz, 2012). This issue can subsequently lead to an inferior final product characterized by a lasting drag on the victims and the community.

2.4.5 Vulnerable population

The vulnerability can be defined as struggling with anticipating, coping, resisting, and recovering from the disaster's impact (Chen et al., 2009). Therefore, vulnerable people’s needs require extra attention to be adequately addressed. The vulnerable population can be divided based on different factors such as age, socioeconomic status, gender, race, and ethnicity, living in densely populated areas, medical issues and disability, (Centers for Disease Control and Prevention, 2015; Hoffman, 2008; Flanagan et al., 2011). For displaced populations, disruptive effects may continue for years as they struggle to return to affected areas (Nakayama, Nicholas Bryner, & Mimura, 2017). Therefore, temporary housing needs to meet these groups' particular needs (U.S. Department of Homeland Security, 2016). In a country with an existing shortage of affordable homes for low-income people (National Low Income Housing Coalition, 2019), the quality of recovery has a decisive role in the condition of these families as overlooking this factor might result in "selective return migration," as Fussel et al. (2010) have pointed out in their research. Today's society consists of a mixture of people from different races and even different languages. This diverse, multi-lingual nature is a source of vibrant multi-culturalism—can also be a source of vulnerability in post-disaster situations (Bolin & Kurtz, 2018).

As Chen et al. (2009) state the needs of vulnerable people, one can discuss how temporary housing can impact vulnerable people's condition. The standards and living conditions of temporary housing have a direct impact on mental health for the vulnerable population, as Sasaki et al., (2018) have discussed in their research. As the assembling process of these types of accommodations is considered time-consuming, in some occasions, people are likely to migrate to adjacent cities to dwell and reside, a choice that sometimes becomes permnent (Myers, Slack, & Singelmann, 2008). In this scenario, people who lived in more vulnerable areas are more likely to leave the affected area. This can result in socioeconomic upset not for the affected region but also the neighboring regions as well. Therefore, how the reconstruction process is planned and executed has a vital role in the long-term sustainability and livelihood of the vulnerable people within the needy community (Schilderman, 2004; Twigg, 2002). Currently, no adequate supervision and attention on the needs of vulnerable and disabled people are in place. As Jachimowicz (2014) has shown in his research, the poverty level has no statistical significance as a factor for planning post-disaster housing by agencies such as FEMA.

2.4.6 Site Planning

After a disaster, all activities regarding creating temporary housing must assess and address land issues, which will vary by disaster and context (Dikmen, 2006; Zhao et al., 2017). Land issues influence the recovery speed from a disaster and can significantly influence the need for and type of transitional housing strategy. This issue can be looked at from different perspective such as land availability, land ownership, the number of evacuees, infrastructure availability, ease of transportation, accessibility, and safe access (Kar & Hodgson, 2008; Kılcı, Kara, & Bozkaya, 2015; Ma, Xu, Qin, & Zhao, 2019; McCarthy, 2012; Nappi, Nappi, & Souza, 2019).

Accessibility is another issue that needs to be considered for selecting a location for creating post-disaster houses (Caunhye, Nie, & Pokharel, 2012). Affected people need to be able to have safe access to any public spaces while they are living in temporary houses. The population's distance should be reachable, especially for the vulnerable population, which was discussed earlier in section 2.2.5. Accessibility not only applies for the people but is also a vital issue for moving equipment and resources, moving often heavy, big equipment over a long distance with compromised routes is considered a challenge.

As researchers such as Zhao et al. (2017) state, site planning is considered as a time-varying demand, which means it is a function of time. This issue is connected with the population density and urban pattern discussed earlier in the paper. There is a need for policies that need to address the identification of temporary housing sites - including supporting water, sewer, electrical, and transportation infrastructure (Smith, 2016). Land scarcity and the need for building multi-story, high-rise temporary housing is yet another issue that needs to be addressed, especially for developed cities. According to FEMA, temporary houses should not be placed in floodplains in order to avert any similar disasters (McCarthy, 2008). Therefore, it encourages the use of mobile homes so that they can be moved to another place in case of emergency. However, as the urban population and density increases, this assumption becomes more unrealistic. Many researchers have focused on developing optimization models and decision-making tools to address the location issue for temporary housing. The models created for managing the site placement for temporal housing can be either single objective models (Ma et al., 2019) or multi-objective (Najafi, Eshghi, & Dullaert, 2013). GIS modeling is another technique in the decision-making process for selecting the location, as different researchers (Kar & Hodgson, 2008; Zerger & Smith, 2003) have addressed in their work. Researchers have proposed a bi-level location-allocation model for the flood evacuation planning with shelter capacity constraints using a genetic algorithm (Kongsomsaksakul, Yang, & Chen, 2005). In this model, the researchers have considered the location problem and the evacuee's preference as two variables of their model. However, other researchers such as Nappi & Souza, (2015) suggests that the location of temporary housing stems from numerous factors such as cultural characters, privacy, and accessibility.

2.4.7 Cost Balance; Transitional Houses vs. Permanent Housing

Transitional housing is currently considered expensive compared to its life span (Lingle, Kousky, & Shabman, 2018). According to a 2017 report from the United States Government Accountability Office, FEMA has spent more than 250 million dollars for sheltering people affected just by Hurricanes Harvey, Irma, and Maria (GAO, 2017). The main goal for the community is to restore the region to its original state and create permanent structures (Hadafi & Fallahi, 2010; Johnson, Lizarralde, & Davidson, 2006). Therefore, creating transitional houses that meet all standards can sometimes lead to financial problems for the affected state and country. The greater portion of the recovery fund to creating transitional houses comes at the expense of the limited budget available for starting permanent housing projects. This can negatively affect the permanent housing structure process, resulting in broader and everlasting impacts on the region and society. On the other hand, overlooking creating transitional houses can also lead to numerous problems as these units are initially designed to be occupied by people for a considerable amount of time. Therefore, there is a need to create a balance between transitional houses and permanent housing in order to create a sustainable, resilient community. On the other hand, allocating more time and budget in permanent housing can create better, more sustainable housing than the previous formation. If planned correctly, the new housings can reduce future devastation through better construction techniques, land-use regulations, and disaster-response plans (Habitat for Humanity, 2012).

2.4.8 Living Condition

Thermal insulation, Health Risks, and air quality are considered as main topics regarding living conditions. When a disaster strikes, keeping the occupants protected from extreme weather conditions & health risks is one issue that needs to be addressed (Thapa, Bahadur Rijal, Shukuya, & Imagawa, 2019). Also, creating an environment that promotes the occupants' well-being is the next step that needs to be addressed. Some of the issues that need to be addressed are air circulation (Yanagi et al., 2013), volatile organic compounds & mold presence (McCarthy, 2012), and acoustic comfort (Nappi et al., 2019).

After a natural disaster occurs, the area is prone to numerous infectious and diseases (American Industrial Hygiene Association, 2017). With the rise of population and density of the region, the increase of infectious diseases will also increase (Murthy & Christian, 2010). Therefore, in order to keep the people safe from the excessive temperatures or issues caused by the natural disaster such distilled water from broken pipes or floods, the type of transitional houses which are used in these areas are of vital importance in order to keep the health and safety of the people. On-site temporary housing can adversely affect the health condition of the people on site. Building these accommodations in place creates dust, pollution, and noise, which can cause harm to people's health (Narvaez, Renteria, Diaz, Sarria-Paja, & Ochoa, 2019).

2.5 Temporary Housing Construction Relations

The author has visualized the categorization of factors and subfactors and how they affect each other in Figure 2.3. As seen in this figure, the two factors are not completely separated from each other, affecting each other. For example, based on the literature, "logistic" which is a physical factor, is affected by the "population density," which is a subset of the "Community Characteristic" factor, which is considered as a social factor. Therefore, the type of units and the materials used for the temporary houses, which leads to the type of shipping, is also affected by "population density," where this factor decides the type of temporary houses.

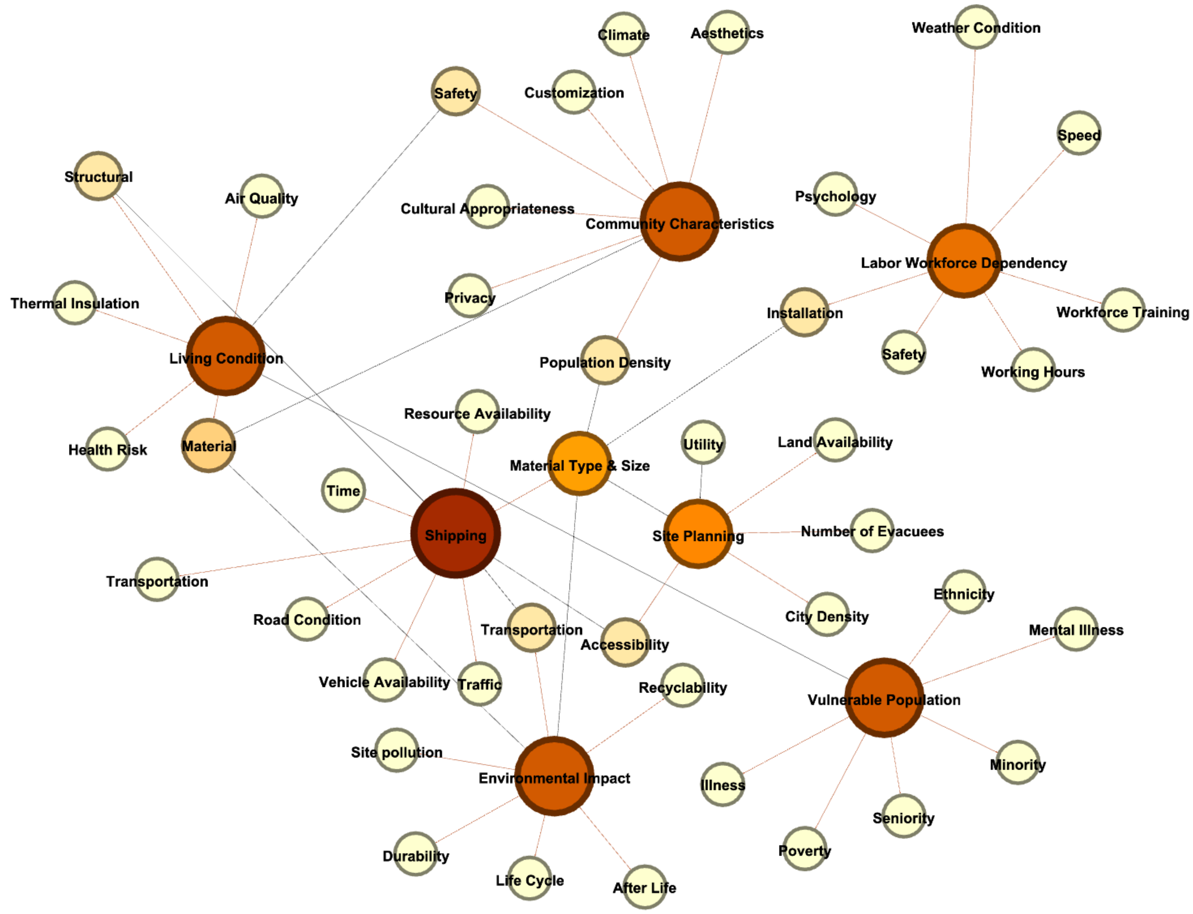


Figure 2.3 Flow and relations of the factors to one another

2.6 Performance Indicator

Factors which impact post-disaster temporary accommodation are subject to bias and personal perception because they lack a robust system for calculation. As a result, a standardized measurement format is needed. A performance indicator is a method that quantifies the performance of two or more elements in separate parts to better compare them. (Pati, Park, & Augenbroe, 2009; Zavadskas, Vilutienė, Turskis, & Šaparauskas, 2014). Several factors affect the built and construction process of temporary houses in post-disaster situations. Performance Indicator has two dimensions—knowledge specificity and time specificity. This keeps the process to date, showing how some factors can be time-varying (Skibniewski & Ghosh, 2009). To measure and quantify these factors, researchers (Afkhamiaghda, M., Elwakil, E., & Afsari, K., 2020) have created a Performance Indicator (PI) index shown in

Table 2.1. This will enable stakeholders to compare the THUs using observable and objective factors, giving them a deeper understanding of the descriptive variables and their consequences when determining the type of THU.

Table 2.1 Performance Indicator

Performance Indicator	Interpretation	Predictor Variables	Reference
Shipping	Type and number of transportation systems that need to be used for assembling the shelter	The Longest dimension of Material, Mass, Ability of the shelter to be broken into smaller parts, Type of Machinery, Type of needed equipment	(Hui Ling et al., 2019; Lopez & Froese, 2016)
Environmental Impact	Amount of material waste, noise, and dust pollution building the shelter and its end life cycle handling.	Reusability, noise and dust pollution, Life span, Flexibility of relocation, Prefabricated foundation	(Escamilla & Habert, 2015; Sener & Altun, 2009; Torus & Şener, 2015)
Community Characteristics	Responding to climate, culture, flexibility with the population density and land area, Sense of identity	Unit flexibility, Aesthetically appealing, User Satisfaction, Responsive to population density	(Bashawri et al., 2014; Kamali & Hewage, 2017; Rufat et al., 2015)
Labor Workforce Dependency	To what degree is the sheltering process dependent on using the human workforce	Number of workers, Construction time, Shelter area	(Escamilla & Habert, 2015; Lopez & Froese, 2016)
Vulnerable Population	To what degree is the shelter responsive to vulnerable groups [children & elderly] and family structures	Ability to be modified for vulnerable people's need	Flanagan et al., 2011
Site Planning	How the temporary housing adapts to the land scarcity in high dense areas and route compromises	Ability to build multi-story shelters compared to the equipment needed, Access to infrastructure	(Smith, 2016; Zhao et al., 2017)
Affordability	The affordability of temporary housing progress without compromising the budget for permanent housing	Summation of material cost, labor cost, shipping cost, finish cost, maintenance cost, and afterlife cost divided by its life span	
Living Condition	To what degree does the shelter promote the well-being of the occupants and protect them	Mold presence, volatile organic compounds presence, air circulation, thermal comfort	(McCarthy, 2012; Thapa, 2019; Yanagi et al., 2013)

2.7 Multi-Objective Decision-Making Tools

Multi-objective decision making (MODM) is considered as choosing an optimal outcome while minimizing the consequences when dealing with multi-parameter issues (Gunantara, 2018; Hwang & Yoon, 1981). However, it is impossible to reach a scenario where all factors are on their optimal performance as these criteria are usually conflicting with each other. (Hayles, 2010; Haymaker et al., 2018; Pati et al., 2009). Thus, it is important to prioritize and weigh the factor based on their importance in the work process to maximize certain design aspects and minimize some of the difficulties.

Prudence, accuracy, and punctuality in making decisions are considered as vital elements as decisions can have consequences (Bellos, 2012). Any wrong decision made can lead to redoing a task and delay in construction (Odeh & Battaineh, 2002), which leads to overruns in terms of time, cost, and quality.

MODM is based on prioritizing different criteria and weighting them to each other. Therefore, having a robust, concrete data collection from similar projects is an integral part of having expert knowledge. This data can be either hard data or expert judgment, or both. However, when using expert judgments, it is essential to create an adaptable model so that it would have the ability to adjust considerably based on region and time of use. As the population grows exponentially, factors will change, issues will become more complex, and imprecise information will lose its functionality. Therefore, systematic data collection is needed in the construction industry sector. This is even more important in the post-disaster construction process due to the restrictions and the environment's situation; data recording can be more challenging.

Researchers approach decision-making in this industry with subjective criteria, where each parameter is defined in a fuzzy environment.

Equation 1 shows the decision-making matrix which is used for the MODM process. There are n available alternatives for a decision, where $N = \{1,2, 3,\ldots,n\}$, and m number of factors that affect the performance of each of the alternatives that can be created for each process, $M = \{1,2, 3,\ldots m\}$, defines the number of rows (Rolland, 2006). In this case, a matrix of n x m will be formed to show the process. Factors can be divided into criteria that directly affect the process and the limitations.

$$\begin{matrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{12}^k & x_{12}^k & \cdots & x_{2n}^k \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{matrix} \tag{1}$$

In this scenario, k is the number of decision-makers or experts where k = {1,2, 3,…, K }. As mentioned earlier, factors and criteria are weighted differently from each other, and their level of importance is different from one another. Each index of the matrices has different measurements, and while some of these can be measured numerically, others may only be evaluated qualitatively. Because of this, a relative weight, noted by W, is given to each of the parameters. It is important to note that as each parameter's size and measurement are different, the weights need to be normalized where the sum of the normalized weights add to one. In an environment where there are k decision-makers, $W_1^k + W_2^k + \cdots + W_n^k = 1$.

As the researcher will be dealing with unlabeled, fuzzy data in this research, there would be an introductory explanation of the proposed methods that will be used in the next section.

2.7.1 Artificial Intelligence

John McCarthy first used the term "Artificial Intelligent" (AI) in 1956 with the idea of machines that can think, and Newell, Shaw, and Simon created the first AI system (McCorduck & Cfe, 2004). It has been reported that 90% of the data has been created just in the last two years (Marr, 2018). Therefore, AI has become a fast-growing technique exponentially taking over all industries in almost every discipline (Press, 2019). AI refers to the idea that machines can learn smartly by duplicating the behavior and learn from the experience. They use a large amount of data to recognize the pattern and the relation between the data.

2.7.1.1 Machine learning

Machine learnings (ML) is a subset of AI that uses statistical methods to enable machines to learn tasks to perform and improve with experience without being explicitly programmed for each task (Mohri, Rostamizadeh, & Talwalkar, 2018). The model In ML systems is created based on past data available. Therefore, an expert need to label and sort all these data so that the system can learn based on them. However, it does not rely on any high-performance machines to operate.

Based on the type of data that is used to train the system, ML methods can be divided into two major classes:

- Supervised:

  In this method, the user trains the model using labeled data, meaning, and input, the output is provided to the system. Using known input and outputs can create a model to forecast an unforeseen scenario (Ghahramani & I.Jordan, 2012). Its main application is for regression and classification as it forecasts outcomes. It is the best use for scenarios where there is available data from previous experience.

- Unsupervised:

  Unlike supervised learning, unsupervised models work on their own to discover information. It mainly deals with unlabeled data.

  Helps with finding the pattern in data by classifying and clustering and allows more complex processing tasks compared to supervised systems (Hastie, Tibshirani, & Friedman, 2009)

2.7.2 K Nearest Neighbor

K Nearest Neighbor (KNN) is a non-parametric classification technique where the system collects all the data and try to group them based on a specific pattern or structure. When a new entry is added to the model, the system will select K– observation from the training set near the new input and classify it based on a similarity measure (Brownlee, 2016; Keller & Gray, 1985). In an n-dimensional space, KNN's learning algorithm stores all instances that correspond to training data points. When it receives an unknown discrete data, it analyzes the closest *k* number of saved instances (nearest neighbors) and returns the most common class as the prediction. It returns the mean of k nearest neighbors for real-valued results. Compared to the other classification techniques, such as Naïve Bayes, KNN is ideal when the sample size for data training is small or missing information regarding the problem domain. As a new data point is defined into the system, the system starts searching the whole training set for the closest similar instances to the new data or its neighbors (Harrison, 2018). Figure 2.4 shows the algorithm model for KNN.

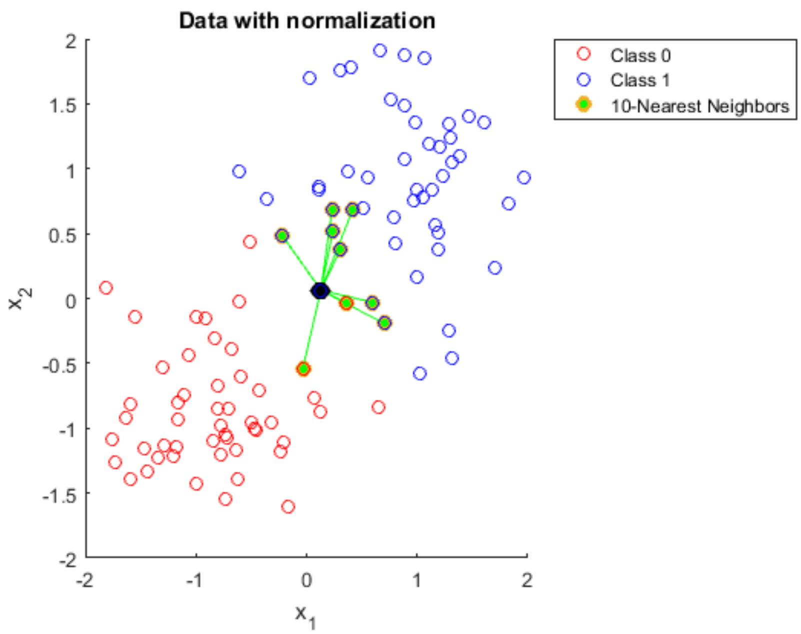


Figure 2.4 K Nearest Neighbor Algorithm Model

K here defines the number of most similar instances (the neighbors). The classification of the new data input will be defined based on its neighbors. Therefore, a low number of K will result in an inaccurate model. The accuracy of the model will increase with increasing the K until it reaches its tipping point, where after that, the system would take a long time to generate the model, and it would reach resource issues. While there is no specific way to select the K value, programmers usually specify K's value by taking a square root of the number of data points. If the square root result is even, they reduce one from it to have an odd number of classes to avoid confusion for the system. Each dataset has its requirements. In the case of a small number of neighbors, the noise will have a higher influence on the result, and a large number of neighbors make it computationally expensive. Based on the *K* value, the system will then start to see how its closet neighbor points' behavior should classify the new point. The Euclidean Distance (ED), shown in Equation 2, is used to find the distances between the new input and existing data points. ED is the most widely used distance function, which is an extension of the Pythagorean Theorem. Using this formula, the system calculates the distances between the new data point (χ) and the existing attributes (x_i) (Prasath et al., 2017).

$$Euclidean\ Distance_{(x,x_i)} = \sqrt[2]{\sum(x_i - x_{ij})^2} \tag{2}$$

2.7.3 AHP

AHP, developed by Saaty, is a common method for solving complex decision problems with multiple criteria (Saaty, 1996). The problem is broken down into a hierarchy of parameters and alternatives in this model to choose the best alternatives (Salem & Elwakil, 2020). In this model, both qualitative and quantitative data can be compared. Each choice will be weighted and graded in AHP based on an expert judgment (Hamali, Suci, Utami, Hanisman, & Arga, 2017). The relative significance of one criterion over another can be expressed using pair wise comparison.

This will assist the decision-maker to track the process's accuracy. AHP believes that the parameters in a set are not dependent on each other (Wu & Tsai, 2012). The framework of the AHP process is shown in Figure 2.5.

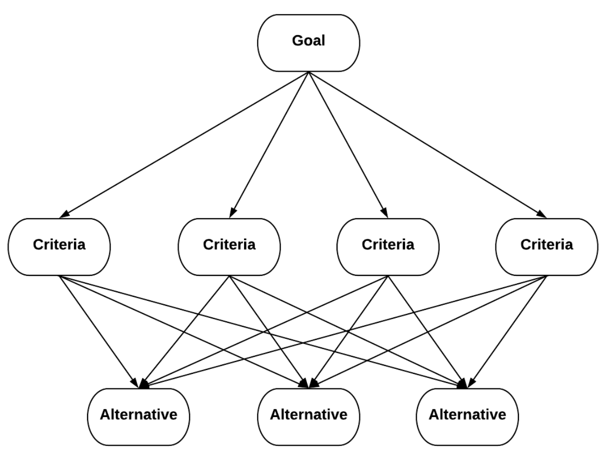


Figure 2.5 Analytical Hierarchy Process Framework

2.8 Research Gap

As this literature review reveals, minimal research has been done regarding reviewing the relationship of nodes affecting the post-disaster temporary housing process and how all these factors and elements are linked together and can affect the process. This is one of the most important research gaps, as selecting the proper type of temporary house for the region can lead to user satisfaction and time and cost saves. Table 2.2 shows an overview of the gaps and issues that post-disaster construction faces.

Table 2.2 Gaps in Post-Disaster Temporary Housing

Factor	GAP	Reference
Shipping	Access to the site might be compromised, Long traffics, Long distance, Big Unit Sizes	(Hui Ling et al., 2019; Lopez & Froese, 2016)
Community Characteristics	Neglecting working with communities in the pre disaster portion to take their input into account. Lack of consideration given to cultural and social concerns serve to reinforce and sometimes-even increase the vulnerability of local communities.	(Bashawri et al., 2014; Boen & Jigyasu, 2005; Kamali & Hewage, 2017; Rufat et al., 2015; Torus & Şener, 2015)
Labor Workforce Dependency	A lack of personnel with ES and disaster expertise The humanitarian sector's slow rate of adaptation to new practices	(Abrahams, 2014; Escamilla & Habert, 2015; Lopez & Froese, 2016)
Risk Reduction	Lack of robust framework in deciding whether the community needs to be rebuilt or relocated Differing mission statements amongst agencies and what designated donated funds can be utilized form Lack of financial resources to afford housing	(FEMA, 2009, 2018)
Population	By Population Increasing and More People Living in Cities, Traditional Frameworks will Not be Responsive	(Félix et al., 2013)
Site Planning	Lands supporting water, sewer, electrical, and transportation infrastructure	(Johnson, 2007; Smith, 2016)
Construction Cost	Currently considered expensive compared to its life span Timeliness in the availability of recovery resources	(FEMA, 2018; Johnson, 2007)
Data	Shelter resident data is collected by multiple agencies No Robust data Collection & data sharing No interoperability of data exchanges No standard data type	(FEMA, 2018; Yu et al., 2018)
Decision Making	No standard format or base of measurement has been defined Subjective decisions change by person, region, time, experience, etc. Large variety of data with different type and format different data sources	(Dikmen, 2006; Hayles, 2010; Rashidi et al., 2011)

2.9 Summary

This chapter has provided a review of research related to post-disaster housing building strategy, post-disaster construction, temporary housing construction criteria, and multi-criteria decision-making tools. The literature shows that minimal research has been done regarding measuring and studying the factors that affect post-disaster temporary housing concerning one another. Previous researches have been limited in considering a limited number of factors. Furthermore, there is an absence of an assessment tool that would reflect the relative importance of each factor in relation to the others.

CHAPTER 3. METHODOLOGY

3.1 Overview of the Methodology

This research is considered developmental research as it develops a tool to assist contractors in creating temporary shelters in the post-disaster situation and decision-making. The research methodology is shown in Figure 3.1. The process contains the subsequent stages: literature review, data collection, verification, conclusion, and recommendations.

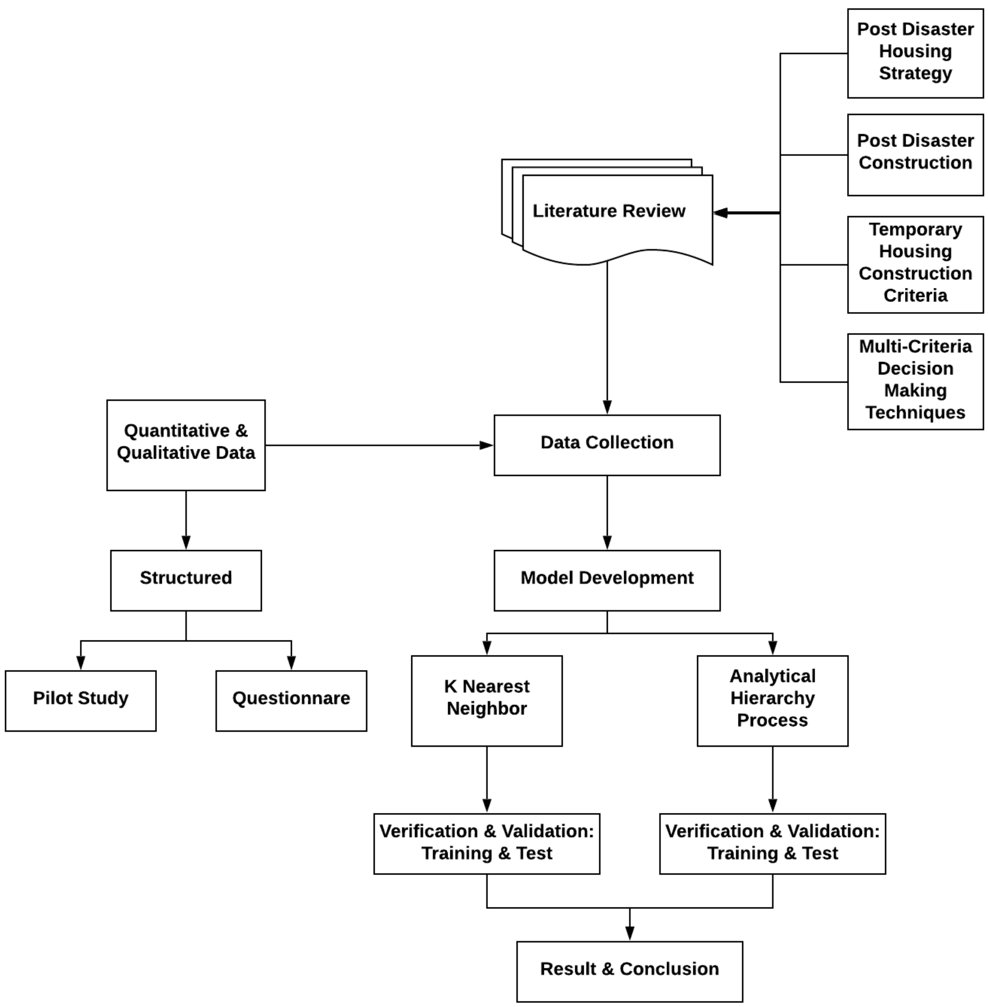


Figure 3.1 Overview of the Research Methodology

3.2 Scope, Population, and Sample

This research study follows a multi-phase sequential mixed-methods approach. In the first stage of the research, the researcher will do a comprehensive literature review to find the main factors affecting temporary shelters' construction process and their weights from all stakeholders' perspectives. Next, surveys will be distributed between key players to find the weights of the factors from all stakeholders' perspectives. The population of the research can be categorized into two different sections. The first group is all the state, federal, and local coordinating officers, which create the joint field offices in the United States. This group is the participants who provide temporary housing to people affected by natural disasters in the country. The second group is all the private and non-governmental groups who create post-disaster temporary housing and vendors and manufacturing companies who generate these lodging units. The keywords for targeting participants for the second group were "disaster risk specialists," "disaster recovery consultants," and "disaster risk managers." To achieve a more comprehensive result, the responders were not limited to a specific position and organization. The population samples will vary in the position and affiliated department. The pilot surveys will be modified and updated several times to address and reflect the remarks and suggestions from various connoisseurs and to ensure the answers are dependable.

Lastly, the researcher moves to the next task, which is creating a multi-objective optimization simulation using the criteria obtained from the previous step, creating each measure as a layer to create the framework.

3.2.1 Variables

This section lists the dependent and independent variables from the data set that were used for the analysis. As mentioned previously in the study, building temporary housing depends on eight main criteria. However, it is integral to the research to point out that each of these variables is affected by numerous sub-factors. The list of each of these independent variables with their corresponding criteria is shown in Table 3.1. For convenience, the researchers have coded the sub-factors responding to each main variable.

Table 3.1 List of Main Variables and their Subfactors

Performance Indicator	**Criteria**	**Code**
Shipping	Transportation	SH-1
	Resource Availability	SH-2
	Time	SH-3
	Vehicle Availability	SH-4
	Road Condition	SH-5
	Traffic	SH-6
Environmental Impact	Durability	EI-1
	Life Cycle	EI-2
	Recyclability	EI-3
	Site Pollution	EI-4
	Transportation	EI-5
Community Characteristics	Climate	CC-1
	Customization	CC-2
	Privacy	CC-3
	Safety	CC-4
	Population Density	CC-5
	Cultural Appropriateness	CC-6
	Aesthetics	CC-7
Labor Workforce Dependency	Installation	LW-1
	Speed	LW-2
	Safety	LW-3
	Workforce Training	LW-4
	Psychology	LW-5
	Working Hours	LW-6
	Weather Condition	LW-7
Vulnerable Population	Seniority	VP-1
	Ethnicity	VP-2
	Minority	VP-3
	Mental Illness	VP-4
	Poverty	VP-5
	Illness	VP-6
Site Planning	Land Availability	LO-1
	Number of Evacuees	LO-2
	City Density	LO-3
	Accessibility	LO-4
Construction Cost	Shipping Cost	CO-1
	Labor Cost	CO-2
	Material Cost	CO-3
Living Condition	Health Risk	LC-1
	Thermal Insulation	LC-2
	Air Quality	LC-3
	Material	LC-4
	Structural	LC-5

The aforementioned dependent variables will be used for creating the AHP model, which was explained earlier in section 2. These variables will be evaluated through a Likert scale by the stakeholders. Therefore, the data collected in this research will be ordinal and holds no precise quantity.

To create a decision-making model for each of the factors listed in Table 3.1, the researcher uses KNN modeling, a supervised classification machine learning. The data for the KNN modeling, just like the data for the AHP, are considered ordinal, which needs to be evaluated and weighted by tacit knowledge.

3.3 Overview of Data Collection

The first step is to determine the general factors that can lead to creating a resilient temporary house. For this mean, the researcher used the “Academic Search Premier" and "Engineering Village" as databases. The search included high-ranked peer-reviewed journals, conference proceedings, and most cited documents. In this step, the researcher will first gather information on "resiliency" and "temporary housing," making these two the primary keywords they searched in the database separately. To broaden the range of search and the information retrieved in the first step, the researchers used the keywords and their synonyms. The other strategy used was using the “OR” logical operator in the database search engine.

Throughout this search, the researcher will apply the selected filters to narrow the scope and get the desired result.

The findings will be a list of numerous factors that can affect temporary housing from the construction point of view. In the next step, the researcher will survey a panel of experts to ensure that the findings are relevant and reliable. Lastly, a questionnaire will be sent to stakeholders and contractors of post-disaster temporary housing to find out the weight and importance of the factors from the experts’ point of view.

3.4 Overview of Data Analysis

As mentioned previously, creating post-disaster temporary housing has many uncertainties by its nature—lack of consideration of subjective variables on the process. Besides, stakeholders in the AEC industry are used to expressing linguistical evaluations and tacit knowledge rather than using hard data. Therefore, the researcher will be employing a supervised machine learning classification and pair wise comparison modeling technique for this matter.

The data analysis for this study can be broken down into two steps:

1 - Create an optimization model based on the predictor variables for each of the Performance Indicators:

Using the temporary housing construction criteria shown in Figure 2.2, the researcher creates a model to understand how and to what degree each of the variables from Table 1 depends on their subfactors. As this model's data is based on tacit knowledge and not hard data, the researcher would use the experts' opinions to create the model. This would help the researcher to implement a factor for each of the performance indicators. The researcher would use python and the "Scikit-learn" library to develop the model.

2- Developing an ML classification model for the entire decision-making process based on performance indicator optimization:

The researcher has set the classification of THU as the outcome. More particularly, classifying THU based on whether they are built on-site or off-site. The outcome is considered a categorical variable where the different values have no real numerical relationship. These types of variables frequently arise in scenarios where the information is based on tacit knowledge. To use these types of data in a machine learning model, which only use numeric data, the data needs to be encoded. For this sake, the researchers have used dummy variables. A dummy variable is an artificial variable created to represent an attribute with two or more distinct categories/levels. applying mathematical operations to them is not valid as they represent an object and not a real numerical value (Zhang et al., 2014). In this scenario, the researcher will use KNN modeling technique in the Python environment. The KNN supervised classification system can train a model that can help the stakeholders with the optimal solution. This process employs the criteria affecting post-disaster temporary housing. Figure 3.2 shows the criteria hierarchy and framework of this model.

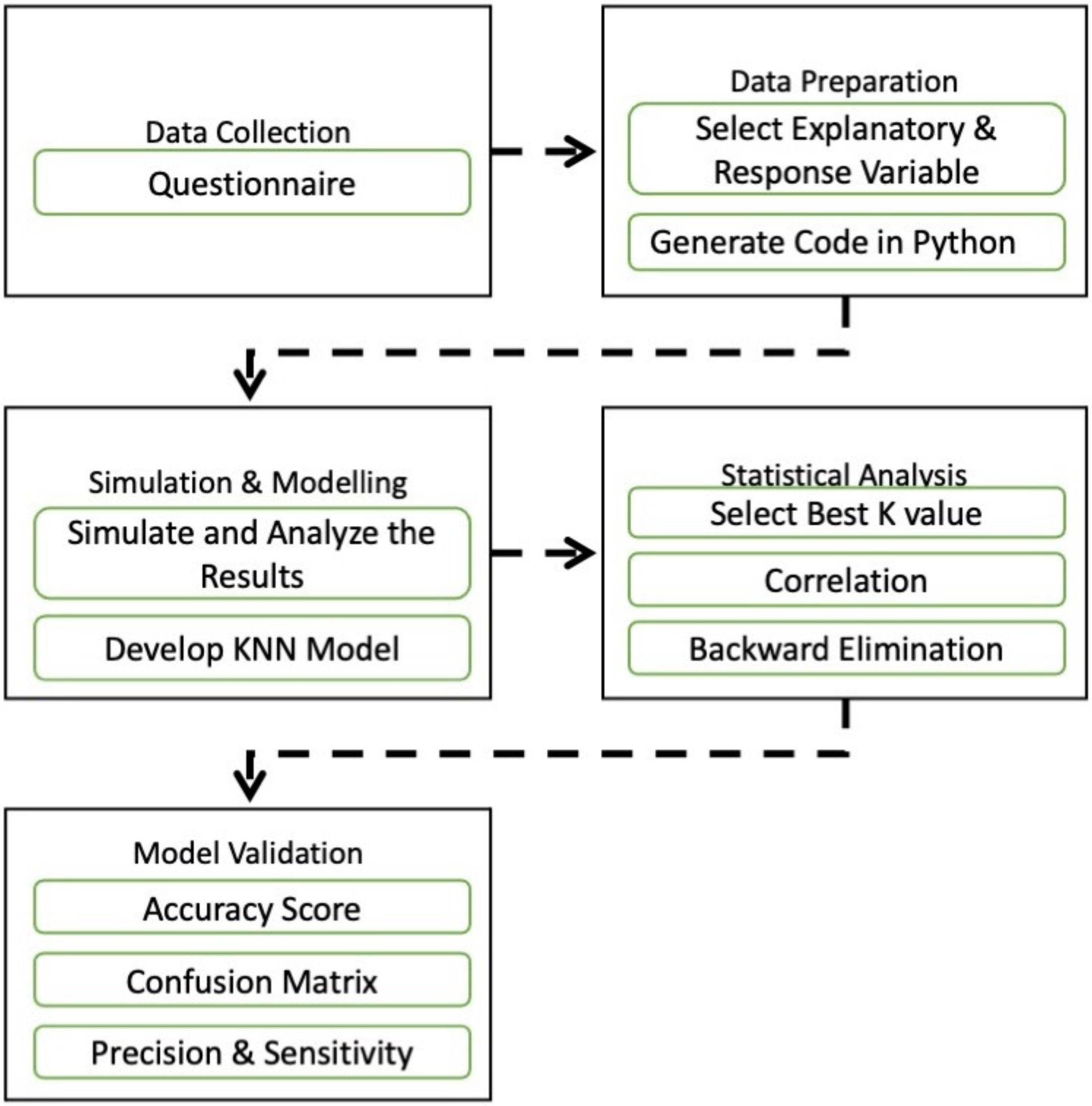


Figure 3.2 Machine Learning Classification Modeling Framework

3.5 Reliability

The researcher plans to perform a pilot study and distribute preliminary surveys between a panel of experts to check the consistency and reality of data and make certain that each question was clear and effective. The panel of experts for this pilot study will be consist of 8-10 people from the industry and academia who have experience in the field. The survey results of the respondents will be tested for reliability using logical consistency measurements. The Consistency Index (CI) and Consistency Ratio (CR) will be used to ensure that the overall priority weights are logically consistent. First, the significance rating's verbal variables will be transformed to a numerical value. Following the conversion of the variable judgments to numerical values, a pair-wise comparison will be formed for each respondent based on their significance ranking. The value of Cronbach's coefficient alpha of the responses will be used to verify the data's reliability.

3.6 Validity

Prior to actually distributing the technique, a team of specialists in the area will examine its face validity to ensure that each question elicits a response that is relevant to asset criticality. Spearman's correlation is "a test measures the strength and direction of the association between two variables that are measured on an ordinal or continuous scale" (Minitab, 2016). To check the validity of the model, the collected data will be divided into two sets, model building (80%) and validation (20%). The validation data that is 20 % will be selected randomly and kept away while modeling the analysis. After finishing the model, the validation data will be used to test the model.

CHAPTER 4. DATA COLLECTION AND ANALYSIS

4.1 Introduction

This chapter provides the framework of the data collection procedure, the targeted population selected for the study, and the validity of the process. This research study follows a multi-phase sequential mixed-methods approach. In the first stage of the research, the researcher conducted a comprehensive literature review to identify the main factors affecting temporary housing's construction process. Figure 2.3 summarizes these major criteria, also known as performance indicators and their sub-factors.

4.2 Expert Based Survey

To collect primary data for creating the model, a set of surveys were distributed between the key players and policymakers of the post-disaster temporary housing to find the weights of the factors from all stakeholders' perspectives. The questions asked from the experts can be grouped into three major sections. First, the researcher asked some demographic questions from each participant. Next, the participants were asked to rank each PI factor. As there are eight main factors in the study, the ranking of the PI elements will be from 1 to 8, with 1 being the most important and 8 being the least important. Lastly, participants used the five-point Likert scale to rate the importance of the different types of temporary houses currently being used, which were extracted from a systematic literature review.

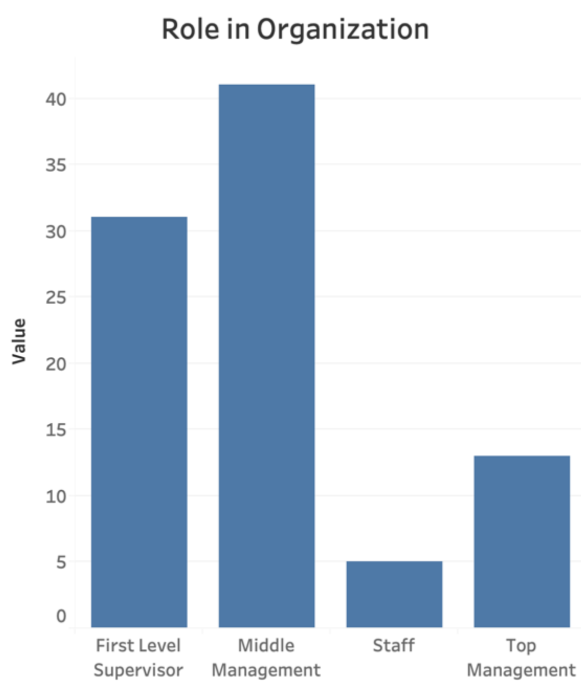
An expedited review by the Purdue University Institutional Review Board (IRB) was received 0n 3/22/2020 with the number of IRB-2020-306, which is shown in Appendix A.

4.2.1 Population and Sample

The study group covered a wide range of participants who provide temporary housing to people affected by natural disasters in the country. The participants' scope of work contained federal, state, and municipal works. To have consistent and reliable results, participants were selected from both the private and public sectors and all firms around the country. The keywords for targeting participants for the second group were "disaster risk specialists," "disaster recovery consultants", and “disaster risk managers.” To achieve a more comprehensive result, the responders were chosen from a wide range of positions, from field workers all the way to top management. The type of organization, the geographical location of the work, and different work level experiences were other factors that the researcher used to have more comprehensive and unbiased responses.

Experts were approached via email and LinkedIn. A total number of 250 questionnaires were sent out to different people, and 94 responses were received. Four of the answers from the dataset were incomplete or had missing values.

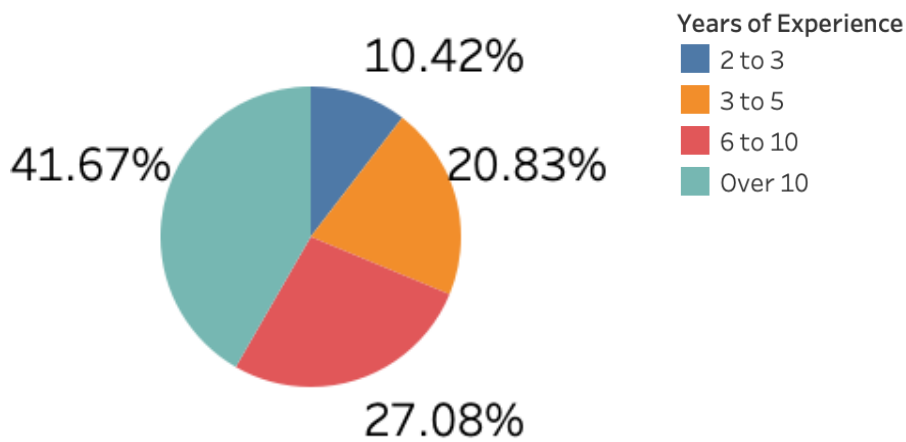
Figure 4.1 A-D shows the distribution of responders based on participants' role, years of experience, work scope, and work's demographic region.



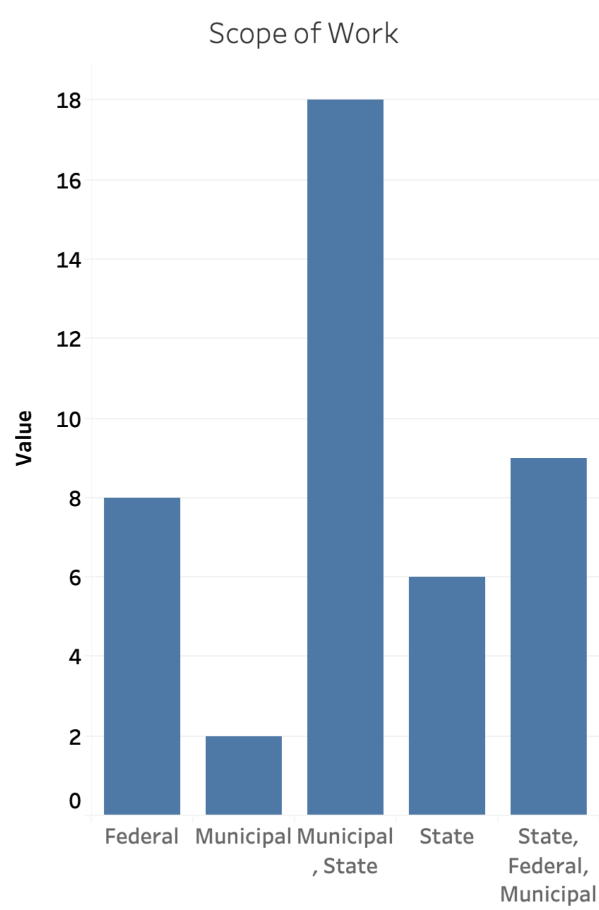
A) Role in Organization

Figure 4.1 Participant Demographic Characteristics

Figure 4.1 Continued

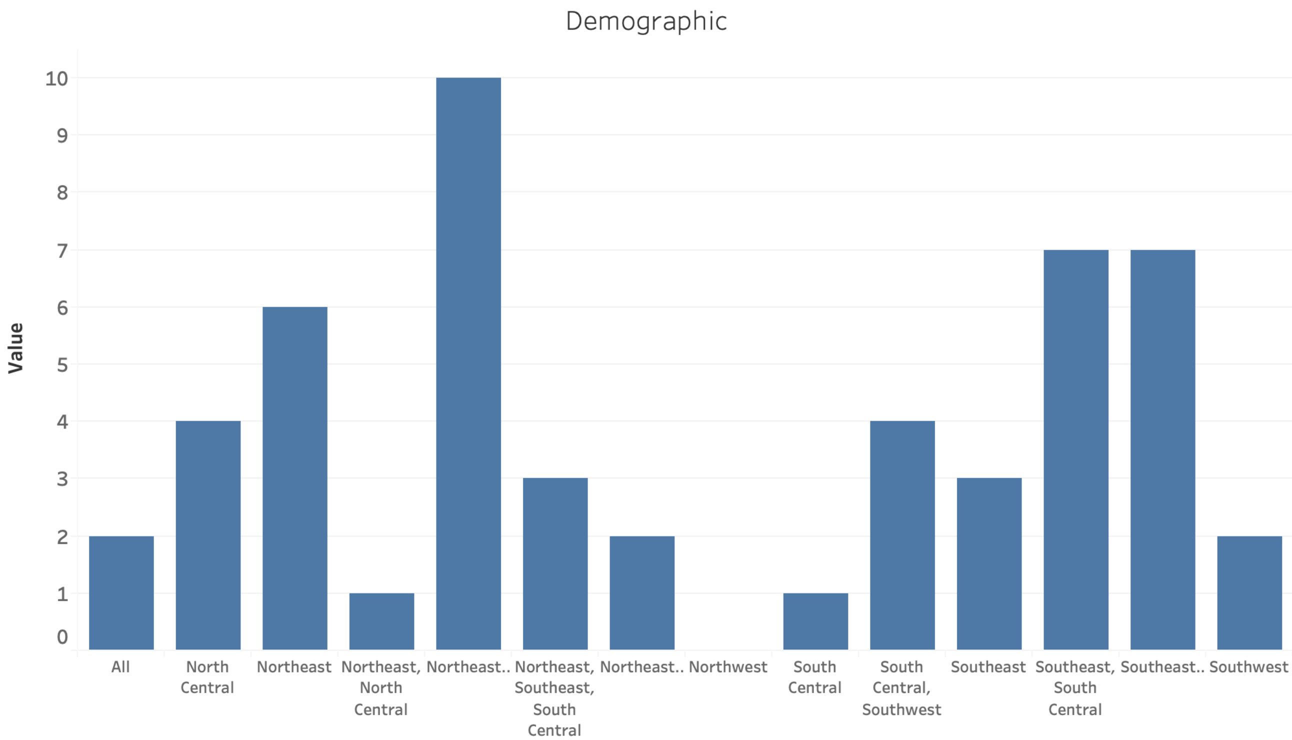


B) Work Experience



C) Scope of Work

Figure 4.1 Continued



D) Demographic Region

As shown in Figure C, many of the organizations' work scope is not limited to just one jurisdiction, and their work and services are performed on different scales. This helps the researcher as the results from these participants would be better representing the whole process.

4.2.2 Survey Questions Reliability and Validity

To measure the internal consistency and reliability of the questionnaire, the researcher has used Cronbach's alpha. The Cronbach's alpha range is between 0.0 and 1.0, with 0 showing no consistency and 1.0 showing perfect consistency in the measurement. The value of Cronbach's alpha can be measured using Equation 3.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{3}$$

In this model, K is the number of components in the questionnaire, X is the sum of individual questions in the questionnaire, σ_X^2 is the variance of the observed total test score, and σ_Y^2 is the variance of each component. The researcher has calculated the Cronbach's alpha for each section of the questionnaire and survey questions individually using Microsoft Excel 2019. The result is shown in Table 4.1. These sections' questions were based on a five-point Likert scale, with 5 being the most important and 1 being the least important.

Table 4.1 Cronbach's Coefficient for Survey Questions

Question Category	**Cronbach's alpha**
Subfactors	0.927
THU	0.705

Face validity was investigated by a panel of subject matter experts in an open debate. Five people with academic and field experience were approached by the researcher. Simulation, disaster reconstruction, emergency response optimization, and data-driven decision-making are all areas of knowledge and focus for this community.

4.2.3 Expert-Based Questions

The questionnaire starts with an explanation of the research's intention, defining the variables, and asking the participants their expert opinion on each variable's relative importance. The full version of the survey can be seen in Appendix B.

The questionnaire can be divided into four major sections. First, demographic questions help the researcher collect and analyze the responders' characteristics with a combination of ordinal and nominal values. Table 4.2 shows each question in this section. These questions help the researcher create a model with a diverse population and, thus, a more accurate, less biased model.

Table 4.2 Data Type and Categories in the Demographic Section

Question	Response Choices
Highest Level of Education	University Graduate
	Some College
	High School
	Less than High School
Organization’s Scope of Work	Municipal
	State
	Federal
Type of Organization	Private Sector
	Governmental
Role in Organization	Top Management
	Middle Management
	First-Level Supervisor
	Staff
	Operational Worker
Years of Experience	Less than 1
	1-2
	3-5
	6-10
	Over 10
Geographic Region of the Organization	Northeast
	Southeast
	North Central
	South Central
	Northwest

As mentioned in section 2.4, eight main factors affect post-disaster temporary housing, while each factor is a function of numerous subfactors. Based on this information, the researcher grouped the subfactors for each main criterion individually and asked the participants to evaluate each sub-criterion for the specific PI in the next section of the questionnaire. These criteria are based on the rating scale, and the responders are asked to rate the importance of these values. As a result, in order to quantify these subfactors, this research develops a Likert scale based on the PI table's understanding to make qualitative meanings quantitative and measurable. The case studies are rated and measured on a scale of one to five, with one being the lowest and five being the highest.

Before deciding on the five-unit Likert scale, the author held an open discussion with a group of subject matter experts to discuss various types of Likert scales and the most suitable scoring for this study. Five people with academic and field experience were approached by the researcher. Simulation, disaster reconstruction, emergency response optimization, and data-driven decision-making are all areas of knowledge and focus for this community. The researchers ask the panel about the importance and clarity of each of the Likert scale options. The researcher explored the three, five, seven, and nine-unit point Likert scales, which are the most commonly used scaling choices. The researcher chose the five-unit scaling method based on the panel's recommendation after consulting with them. The researcher also relied on the literature review, which found that having a large number of options would lead to a low response rate. The responders were asked to evaluate each sub-criteria of the performance indicators on a Likert scale, ranging from 1 to 5. The values in the ranking represent “not important at all,” “slightly important,” “important,” “fairly important,” “most important,” respectively. Figure 4.2 shows the example of this question for one of the PI factors.

2. **Decision-Making Factors Identification and Assessment**

From the list provided, please evaluate each factor based on their importance from 1 = not important at all, 2 = slightly important, 3 = important, 4 = fairly important, 5 = most important.

Shipping

	1	2	3	4	5
Transportation	○	○	○	○	○
Resource Availability	○	○	○	○	○
Time	○	○	○	○	○
Vehicle Availability	○	○	○	○	○
Road Condition	○	○	○	○	○
Traffic	○	○	○	○	○

Figure 4.2 Rating the Subfactors for Each Performance Indicator

Figure 4.3 shows the boxplot for each subfactor according to the PI. This plot shows the spread and distribution of the answers and where most of the data is. Boxplots typically graph six data points:

- The lowest value, excluding outliers
- The first quartile (this is the 25th percentile or median of all the numbers below the median)
- The median value (equivalent to the 50th percentile)
- The third quartile (this is the 75th percentile or median of all the numbers above the median)
- The highest value, excluding outliers
- Outliers

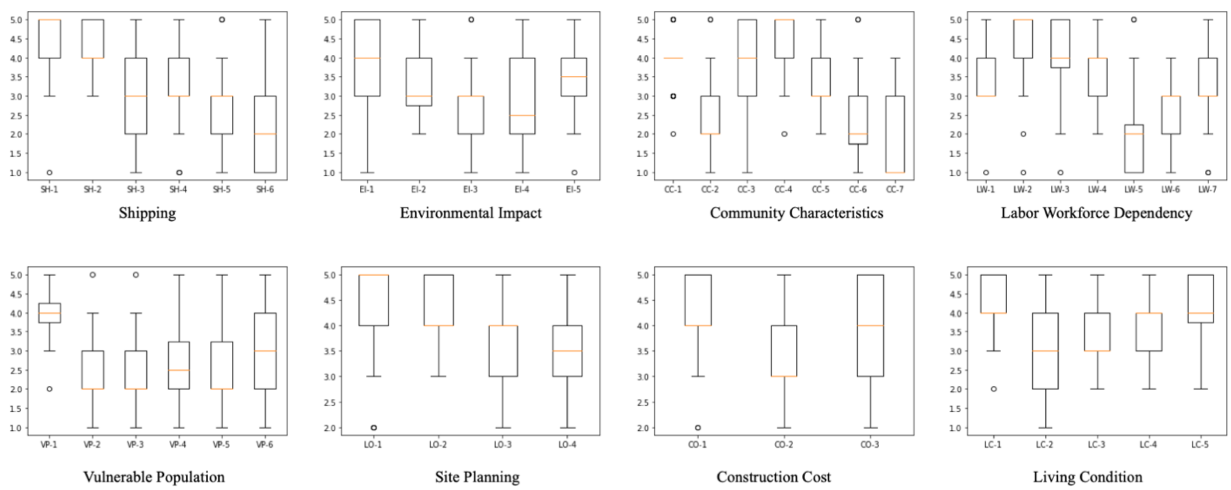


Figure 4.3 Boxplot of Subfactors Response Distribution

For example, the data analysis from the boxplot shows that 50 percent of the answers for the fourth subfactor in the “Shipping” PI (Vehicle Availability) lies between 2 and 3. This indicates that this subfactor is not considered as highly important for most policymakers. On the other hand, subfactors such as “Transportation” and “Resource Availability,” shown as SH-1 and SH-2 respectively, have answered 75% between 4 and 5 with the lowest value of 3. This shows that these subfactors are considered as most important variables for all policymakers. Appendix C shows the descriptive analysis for all the subfactors, including the median, mode, and standard deviation for the relative importance ratings based on their PI.

The next section of the survey consisted of participants rate the importance of different types of current temporary houses used from 1, being the least important, to 5, being the most important, as shown in Figure 4.4. For convenience to the participants and clearance, the question provides an image reference with each type of THU label.

Please rate the importance or usage of the following type of temporary house from 1 = not at all, 2 = seldom, 3 = Occasionally, 4 = Often, 5 = always.

Note: Please see figure below for a reference on type of the temporary houses.

	1	2	3	4	5
Steel-framed	○	○	○	○	○
Timber-framed	○	○	○	○	○
Superadobe	○	○	○	○	○
Bamboo	○	○	○	○	○
Panelized Homes	○	○	○	○	○
FEMA Trailers	○	○	○	○	○
3D Printed	○	○	○	○	○
Containers	○	○	○	○	○
Manufactured Homes	○	○	○	○	○
Prefabricated Modular	○	○	○	○	○

Figure 4.4 Rating Different Types of Temporary Housing Units

Table 4.3 shows the descriptive analysis of the aforementioned question which contains the median, mode, and standard deviation value for the relative importance ratings of the different THU. The difference in the units in terms of usage can be clearly seen here as the most selected answer for THUs like “Manufactured Homes,” and “FEMA Trailers” are 5 while the most common answer for the importance of “Bamboo,” “Superadobbe,” and “3D Printed” THU was 1. which insinuates that the variables are all equally important. All analogies had a low standard deviation, indicating a low importance rating variability.

Table 4.3 Descriptive Analysis for Temporary Housing Units

	Steel-framed	Timber-framed	Superadobe	Bamboo	Panelized Homes	FEMA Trailers	3D Printed	Containers	Manufactured Homes	Prefabricated Modular
Count	90	90	90	90	90	90	90	90	90	90
Mean	3.04	3.15	1.54	1.49	2.92	3.85	1.84	3.04	3.52	2.83
Std	0.96	1.18	0.75	0.79	0.96	1.29	0.86	1.27	1.31	1.10
Min	1	1	1	1	1	1	1	1	1	1
25%	2	2	1	1	2.5	3	1	2	3	2
50%	3	3	1	1	3	4	2	3	4	3
75%	4	4	2	2	4	5	2	4	5	4
Max	4	5	4	4	5	5	5	5	5	5
Mode	4	4	1	1	4	5	1	4	5	3

Figure 4.5 shows the radar chart for each of the THU. This shows the relative importance of each THU in the eyes of policymakers. The values are the average of all the responder’s data. It can be seen based on policymakers’ response, “FEMA Trailer”, “Manufactured Homes,” and “Container” are considered as the top three important types of THU in the event of post-disaster.

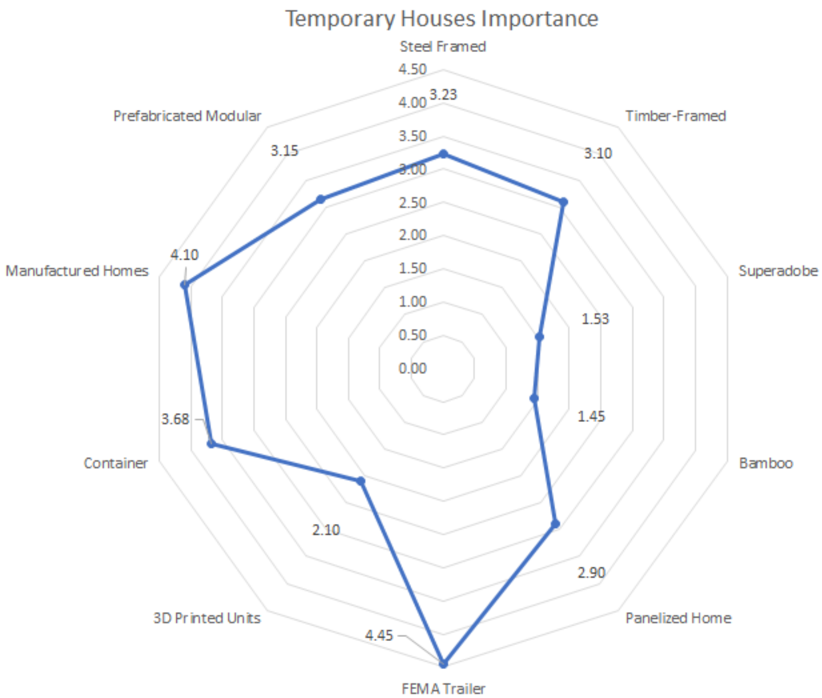


Figure 4.5 Temporary Housing Importance Radar Chart

As mentioned earlier in section 3.4, this study's outcome is the THU classification type, more particularly, classifying THU based on whether they are built on-site or off-site. The researchers have divided these temporary housing based on where they have been built, either on-site or off-site, which is shown in Figure 4.6.

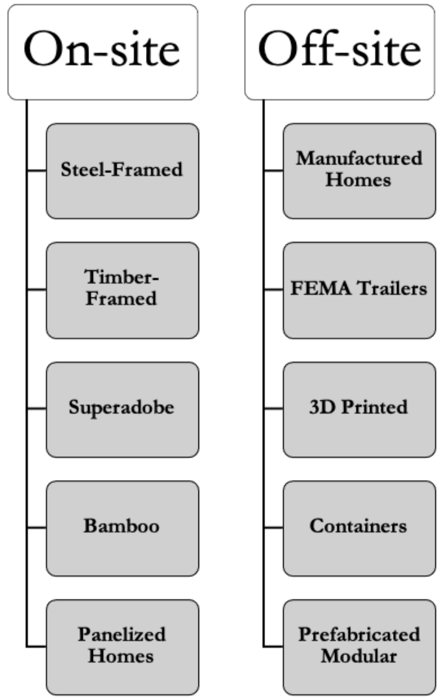


Figure 4.6 Different Temporary Housing Units Based on Classifications

The last section of the questionnaire seeks the participants to rank each of the PI values compared to each other based on their importance, as shown in Figure 4.7. The data type will be an ordinal variable. This would be used as the features or independent variables for creating the ML classification model for the entire decision-making process based on performance indicator optimization.

Please rank the following factors in the order of importance -most important item at the top-, in the process of choosing the type of temporary house for a region by dragging each factor.

1. Shipping
2. Environmental Impact
3. Community Characteristics
4. Labor Workforce Dependency
5. Vulnerable Population
6. Logistic
7. Construction Cost
8. Living Condition

Figure 4.7. Rating Performance Indicator Variables based on Importance

The ranking of the variables is considered as absolute values. Thus, the researchers treated the ranking of features as continuous variables in the study and inversed the rankings to use them in the model. Table 4.4 depicts the descriptive analysis for the relative importance ratings for each of the features. It can be seen that the vulnerable population has the lowest mode and Logistic have the highest, meaning that these two factors are the least and most important factors in the policymakers' eye, respectively. The table also shows numerical data distribution and skewness by displaying the data quartiles (or percentiles) and averages.

Table 4.4 Descriptive Analysis for Performance Indicators

	Shipping	Environmental Impact	Community Characteristics	Labor Workforce Dependency	Vulnerable Population	Logistic	Construction Cost	Living Condition
Count	90	90	90	90	90	90	90	90
Mean	0.55	0.21	0.19	0.24	0.28	0.63	0.36	0.25
Std	0.34	0.09	0.12	0.12	0.27	0.31	0.24	0.19
Min	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
25%	0.225	0.14	0.14	0.17	0.13	0.5	0.225	0.14
50%	0.5	0.17	0.14	0.25	0.17	0.5	0.33	0.2
75%	1	0.2	0.17	0.25	0.225	1	0.33	0.25
Max	1	0.5	1	1	1	1	1	1
Mode	1	0.2	0.14	0.25	0.13	0.5	0.33	0.25

In order to compare the standard deviations, the researchers have used the coefficient of variance or CV, which is a measure of relative variability. Equation 4 shows the calculation method for CV:

$$CV = \frac{std}{mean} \tag{4}$$

While the CV of all comparisons was relatively low, the CV for "Community Characteristics" and "Vulnerable Population "is higher than 1, which indicates a high importance rating variability. Larger CV values indicate that the values in the dataset are farther away from the mean.

4.3 Summary

The data collection procedure for this study is described in this chapter. The data was collected through an expert-based survey from policymakers in post-disaster temporary housing in the United States. The collected data was used to develop the optimization model based on the predictor variables and which will be described in the subsequent chapters.

CHAPTER 5. RANKING PERFORMANCE INDICATOR'S SUB-FACTORS

5.1 Introduction

This chapter describes how the researchers used the collected data from the expert-based questionnaire survey and the Analytical Hierarchy Process (AHP) to determine the relative weight for each subfactor of the PI factors. Using pairwise comparison, one criterion's relative importance over another was evaluated separately for each PI. This evaluation was performed by expert policymakers using a Likert scale evaluation.

5.2 AHP Framework

Step 1: AHP Framework

The AHP model to rank and shortlist the sub-factors affecting the post-disaster temporary housing. The outcome of the systematic literature review shows that building temporary housing depends on eight main factors. However, it is integral to the research to point out that each of these variables is affected by numerous sub-factors. Figure 2.2 outlines the significant variables and the criteria for each of these main variables. For the study's ease, these criteria would be referred to as subfactors, and the main variables would be referred to as Performance Indicators (PI) for the rest of the research. Eight separate AHP model, based on the subfactor variables from each PI was created.

The problem was broken down into a hierarchy of criteria and three main levels, as shown in Figure 2.2. The first level is the main objective of the factors that is assessing the post-disaster temporary housing performance. Level two represents our eight main factors or PI (i.e., shipping, environmental impact, community characteristics, labor workforce dependency, vulnerable population, site planning, construction cost, living condition). The last level, which are the sub-factors with 43 elements, are used to create the AHP model.

Step 2: Pair-wise Comparison

To determine each element's relative ranking, a $j \ x \ j$ square matrix, where j is the number of subfactors of each group, was created for each of the factors to represent each predictor variable. The author first averaged the responses of all the participants in each feature. Next, the matrix was filled where each cell represents the proportion of the corresponding column and the row factors. For example, the value in cell 13, which is the first row and third column, is the first variable's proportion divided by the third variable. Table 5.1 shows the pair-wise comparison for the "Shipping" Subfactor.

Table 5.1 Pairwise Comparison Matrix for the "Shipping" Performance Indicator

	SH-1	**SH-2**	**SH-3**	**SH-4**	**SH-5**	**SH-6**
SH-1	1	1.075	1.433333	1.330077	1.535714	1.954545
SH-2	0.930233	1	1.333333	1.237281	1.428571	1.818182
SH-3	0.697674	0.75	1	0.927961	1.071429	1.363636
SH-4	0.751836	0.808224	1.077632	1	1.154605	1.469498
SH-5	0.651163	0.7	0.933333	0.866097	1	1.272727
SH-6	0.511628	0.55	0.733333	0.680505	0.785714	1

Step 3: Assigning Priorities

Using pairwise comparison, one criterion's relative importance over another was evaluated separately for each PI using eigenvector value. As discussed earlier, this evaluation was performed by expert policymakers using a Likert scale evaluation. First, the pairwise matrix is squared; next, the summation of rows is calculated and then normalized. This cycle continues until the difference between the sums in two consecutive calculations is smaller than a prescribed value. Table 5.2 and Table 5.3 show the pairwise comparison's square matrix and the criteria normalized weight for the "Shipping" subfactor, respectively. The process of creating pairwise comparisons and assigning weights and priorities for the rest of the subfactors based on their PI is shown in Appendix D.

Table 5.2 Square Matrix of the “Shipping” Pairwise Comparison

	SH-1	SH-2	SH-3	SH-4	SH-5	SH-6
SH-1	5.999999498	6.449999453	8.599997416	7.980463132	9.214283293	11.72727029
SH-2	5.581395564	6.000000224	7.999998573	7.423687541	8.571427365	10.90908998
SH-3	4.186046518	4.500000001	5.999998707	5.56776545	6.428570286	8.181817179
SH-4	4.511016843	4.8493431	6.465789405	6.000001102	6.927631767	8.816986371
SH-5	3.906976941	4.200000207	5.599999068	5.196581341	5.999999227	7.636363074
SH-6	3.06976756	3.300000123	4.399999215	4.083028148	4.714285051	5.999999487

Table 5.3 Normalized Criteria Weight for the “Shipping” subfactors

Criteria Weight	Normalized
49.97201308	0.220141436
46.48559924	0.204782756
34.86419814	0.153587061
37.57076859	0.165510301
32.53991986	0.143347931
25.56707958	0.112630516

The weights for each sub-factor (Wi) are shown in Table 5.4. The higher Wi value indicates that the specific parameter is more significant and contributes to the statistical model.

Table 5.4 Sub factor weights (Wi) for the main factors

Performance Indicator	Criteria	Weight Eigen Vectors
Shipping	Transportation	0.2201
	Resource Availability	0.2048
	Time	0.1536
	Vehicle Availability	0.1655
	Road Condition	0.1433
	Traffic	0.1126
Environmental Impact	Durability	0.2302
	Life Cycle	0.2143
	Recyclability	0.1714
	Site Pollution	0.1714
	Transportation	0.2127
Community Characteristics	Climate	0.1727
	Customization	0.1132
	Privacy	0.1784
	Safety	0.2047
	Population Density	0.1538
	Cultural Appropriateness	0.1018
	Aesthetics	0.0755
Labor Workforce Dependency	Installation	0.1502
	Speed	0.1864
	Safety	0.1777
	Workforce Training	0.1480
	Psychology	0.0855
	Working Hours	0.1125
	Weather Condition	0.1396
Vulnerable Population	Seniority	0.2378
	Ethnicity	0.1372
	Minority	0.1326
	Mental Illness	0.1540
	Poverty	0.1555
	Illness	0.1829
Site Planning	Land Availability	0.2796
	Number of Evacuees	0.2730
	City Density	0.2270
	Accessibility	0.2204
Construction Cost	Shipping Cost	0.3687
	Labor Cost	0.2857
	Material Cost	0.3456
Living Condition	Health Risk	0.2258
	Thermal Insulation	0.1665
	Air Quality	0.1877
	Material	0.2013
	Structural	0.2187

Step 3: Logical Consistency

The researchers perform the consistency analysis to check the influence and bias of responders and verify the pairwise matrix consistency. Equation 5 and Equation 6 show how to calculate the Consistency Index (CI) and Consistency Ratio (CR) for each PI, respectively (Fares & Zayed,2010).

$$CI = \frac{\lambda_{max} - m}{m - 1} \qquad (5)$$

$$CR = \frac{CI}{RI} \qquad (6)$$

In these equations, CI is the matrix consistency index, m is the matrix's size, and λ max is the maximum eigenvalue. RI is the random consistency index, which is a constant value based on the matrix's size. Table 5.5 shows the CI and CR value for each PI value. According to these data, all the matrices are consistent, as their CR value is less than 0.1.

Table 5.5 Consistent Index and Consistency Ration for Each PI

m	Variables	Consistency Index	Consistency Ratio
6	Shipping	-2.9245E-08	-2.35847E-08
5	Environmental Impact	1.19402E-07	1.06609E-07
7	Community Characteristics	2.76124E-08	2.09185E-08
7	Labor Workforce Dependency	8.22091E-09	6.22796E-09
6	Vulnerable Population	-1.58379E-08	-1.27725E-08
4	Site Planning	7.46119E-09	8.29021E-09
3	Construction Cost	1.15677E-07	1.99442E-07
5	Living Condition	6.57084E-08	5.86682E-08

As all the PI variables contain consistency, the variables were ranked to determine the relative importance of the variables and those that affect their PI the most. Using the relative weight, the researcher sorted the subfactors based on their importance in descending order. With the idea of creating a shortlist of the most significant variables for each group, the difference of each Wi with its previous value was calculated. A threshold was set as a filter for selecting the number of variables. The final variables are the ones in which the difference between them and the preceding value was lower than the threshold. The results are shown in Table 5.6.

Table 5.6 Most Critical Sub-factors for Each Performance Indicator According to Weight

Performance Indicator	Criteria	Weight Eigen Vectors
Shipping	Transportation	0.2201
	Resource Availability	0.2048
Environmental Impact	Durability	0.2302
	Life Cycle	0.2143
	Transportation	0.2127
Community Characteristics	Safety	0.2047
Labor Workforce Dependency	Speed	0.1864
	Safety	0.1777
Vulnerable Population	Seniority	0.2378
Site Planning	Land Availability	0.2796
	Number of Evacuees	0.2730
Construction Cost	Shipping Cost	0.3687
	Material Cost	0.3456
Living Condition	Health Risk	0.2258
	Material	0.2013
	Structural	0.2187

5.3 Summary

This chapter established the rankings of PI subfactors using the AHP approach from the expert-based survey. Using the expert opinion of policymakers in post-disaster temporary housing, derived from the questionnaire, the researcher prioritized and shortlisted the sub-factors for each main PI. The AHP was structured to identify the factors' weights. This would help develop a model to predict the THU's performance based on these critical success factors. It outlines how currently factors affecting post-disaster temporary housing is biased as the whole process is based on tacit knowledge. It also tackles how some factors are overlooked in the current process. The outcome of this procedure will then be used to develop the integrated AHP/KNN for the THU model, as explained in the next chapter.

CHAPTER 6. K NEAREST NEIGHBOR (KNN) MODELING

A portion of this chapter is pending publication in the Journal of Emergency Management.

6.1 Introduction

This chapter presents the decision-making model that classifies the THU type based on the factors and their importance by policymakers. The model is developed using the tacit knowledge-based information gathered from the professional-based questionnaire from policymakers in post-disaster THU in the USA. The results of this questionnaire were used as input data to develop the AHP/KNN Integrated supervised classification model. The classification model's purpose was to guide policymakers' estimates and administrations' judgments related to choosing the correct type of THU based on their priorities. The model's validity was checked and tested to indicate its applicability to the industry.

6.2 Feature Reduction

Machine learning and deep learning algorithms learn from data, which consists of different types of features. A machine learning algorithm's training time and performance depend heavily on the features in the dataset. Therefore, the ideal goal in ML modeling is to only keep the features in the dataset that actually help the model to learn. Although the raw dataset will cover various features, it is important to remember that not all features will be helpful in developing the model for machine leering. In reality, using some of the features may even have a negative impact on our model. So, in developing a machine learning model, feature selection plays a huge role. The investigator, therefore, decreases the number of characteristics based on their results. There are three explanations for this operation. First, it decreases data overfitting, which implies less ability to make decisions based on redundant data/noise. Then, it increases the model's overall performance, and ultimately, fewer data to deal with reduces the model's training time.

6.2.1 Correlation

The researcher first tested the association between each factor to omit the redundant characteristics, seen in Figure 6.1. Correlation is a statistical term that calculates the degree to which two variables shift concerning each other. Correlation tests association, but it does not indicate whether x causes y or vice versa, or if a third, possibly unknown, element causes the association. However, suppose two or more of the two characteristics are mutually correlated. In that case, they provide the model with redundant information, and, thus, only one of the correlated characteristics should be retained to minimize the number of characteristics. For the correlation test, the researchers set a threshold of 0.8. This suggests that the researcher would only use one of the model variables if two variables correlated 0.8 or higher and ignore the other one.

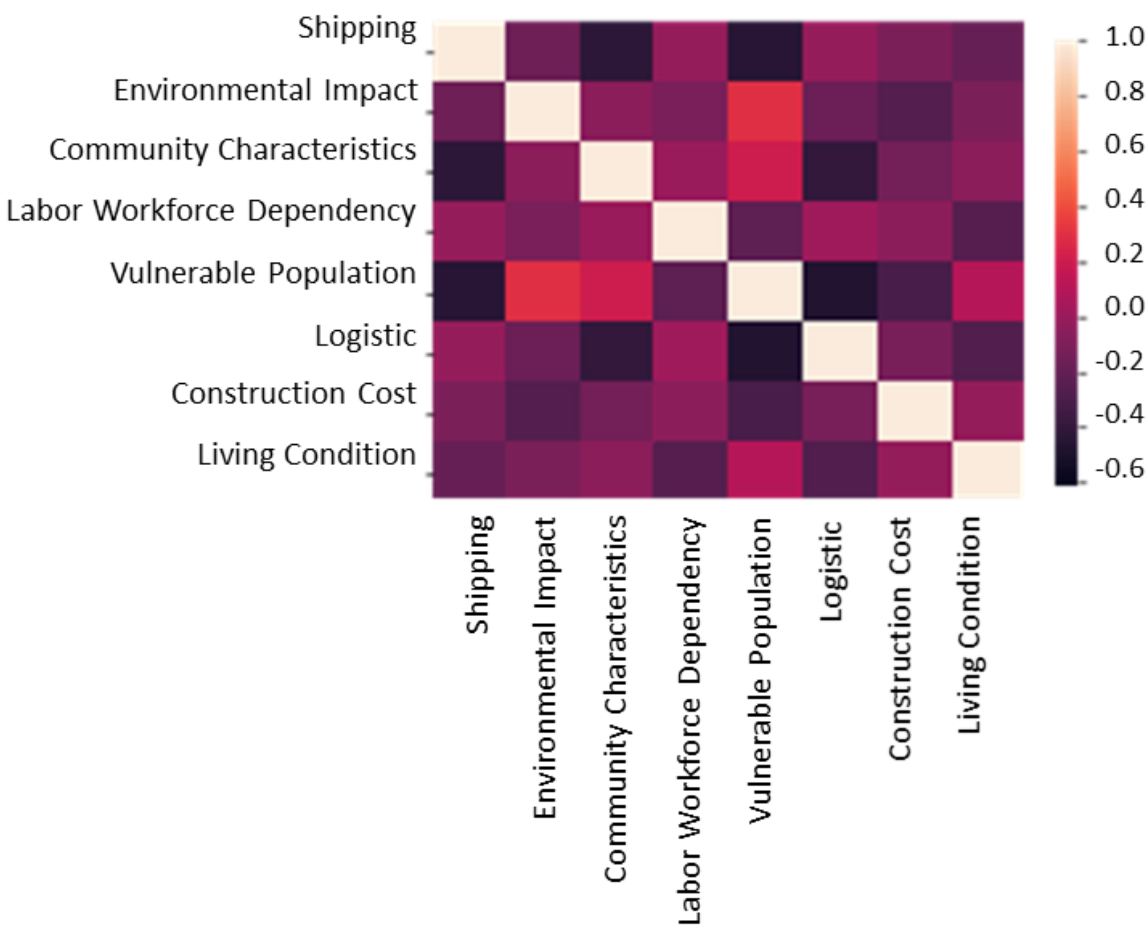


Figure 6.1. Independent Variables Correlation in Regard to Each Other

6.2.2 Backward Elimination

As the model is using continuous data as independent variables and the categorical data type as an outcome. The researcher employed the backward elimination technique to remove the features with no statistical significance on the output to create the most accurate model. The researchers first created the model for all the independent variables in this system and then deleted variables with the lowest p-values one by one until there is no noticeable difference in the model accuracy. To achieve this, the researcher managed a t-test on the variables to measure the *p*-value. It is worth mentioning that the researchers use 0.05 as the level of significance in this research. Table 6.1 shows the p-value for each variable. The t-test was performed sequentially, wherein in each step, the feature with the highest p-value bigger than 0.05 was omitted. This series continued until there was no feature with a p-value higher than 0.05 was left in order to create a more accurate model. A p-value is a measure of the probability that an observed difference could have occurred just by random chance. The lower the p-value, the greater the statistical significance of the observed difference.

Table 6.1 p_value for the independent variables

Variable	P-value
Shipping	4.13585468e-05
Environmental Impact	1.97203337e-01
Community Characteristics	7.36054922e-08
Labor Workforce Dependency	4.60004748e-01
Vulnerable Population	2.15237625e-06
Site Planning	3.29743998e-08
Construction Costs	5.62271364e-01
Living Condition	8.97346499e-03

6.3 Developing the Classification Model

To create the supervised ML classification model, the researcher has used the SKlearn library in the Python 3.7.1 environment using the "Google Colab" platform. This library is used for creating classification, regression, and clustering algorithms. As mentioned earlier, the output of the models in this research is the type of the THU. This output will only contain two discrete values (0 and 1), representing the type of THU. Thus, the output of the model is categorical, where although the output is represented by discrete values ("0" Off-site and "1" for On-site THU), there is no mathematical value to the variable.

If the model is trained based on the whole dataset, it would be overfitting. This happens when the function is too closely fit for a limited set of data points (Kenton, 2019). In this scenario, the model would not be able to generalize since it was only trained and tested on the training data. When it is exposed to a new dataset, it will show a high spread and variance in the results, leading to high prediction error. To validate an ML model's performance, the model will use the Train/Test Split approach. In this research, 80 % of the main dataset data will be randomly selected and then allocated to the training dataset for creating the KNN model. The remaining 20 % was saved for the test dataset to validate the ML model.

When a new data point is given to the model, its type and classification will be determined based on the classification of a group of adjacent existing data points. The quantity of the existing adjacent data points (neighbors) that the model would decide the classification based on is represented by k in the KNN classification. The quantity of k has a direct effect on the model's accuracy. If the k is too small, the model's result would be affected by noise, leading to an inaccurate model. As the k value increase, the model becomes more accurate, and the computational time increases. This tradeoff continues to a certain tipping point where the system would take a long time to generate the model, and it would be computationally expensive. In order to select the most optimal k value, the researcher has used cross-validation to use the best tuning parameter for k that best generalizes the data. Figure 6.2 shows how the model accuracy fluctuation with the change in k value in the range of k = (1,15).

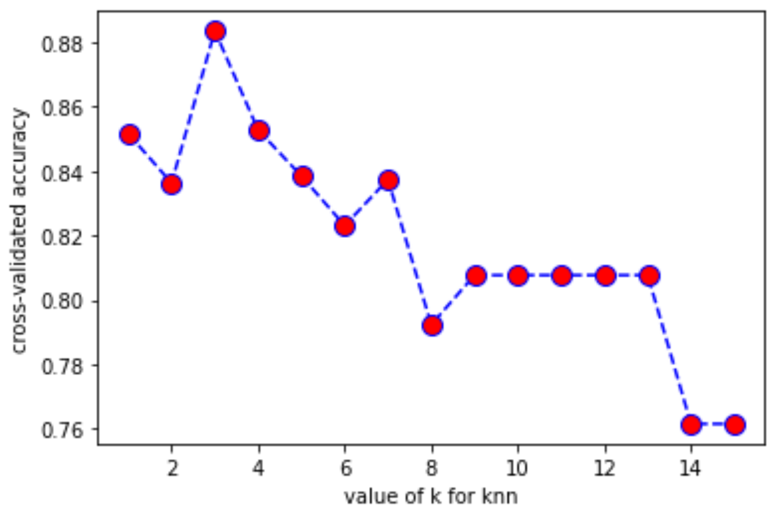


Figure 6.2 Cross-Validated Simulation for K value

6.4 Developed KNN Model Validation

6.4.1 Mathematical Validation

The next step after generating the classification model is to evaluate its functionality. This is usually done through computing accuracy scores. It does not, however, define the type of mistakes the model is making. Thus, it is also important to know the performance of the system to assess the classifier. For this mean, Confusion Matrix, which shows the type of prediction results vs. the actual values on a classification problem (Visa et al., 2011), is used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It depicts the number of actual and predicted values for each class in a 2x2 matrix. Figure 6.3 shows the framework for the confusion matrix.

		Predicted Class	
		Positive	Negative
Actual Class	Positive	TP	FN
	Negative	FP	TN

Figure 6.3 Confusion Matrix Framework

Based on the real and expected values, the system will make two forms of accurate predictions as well as two incorrect predictions. The language of each confusion matrix cell is as follows:

True Positive (TP): The actual value is positive, and the predicted is also positive.

False Negative (FN): The actual value is positive, but the predicted value is negative.

True Negative (TN): The actual value is negative, and the predicted is also negative.

False Positive (FP): The actual value is negative, but the predicted value is positive.

The first parameter that can be achieved using the confusion matrix is the accuracy, which indicates how often a classifier is exact in predicting the correct outcome. Equation 7 shows the formula for accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (7)$$

However, it can be inaccurate to focus entirely on the accuracy value. Based on the model's application and the area of use, it is necessary to determine the type of errors the model produces. Thus, by specifying other parameters, it is vital to demonstrate the various types of errors the model may have. Two of the considerations that can help to test the models properly are sensitivity and accuracy. Sensitivity is the proportion of correct predictions when the actual value is positive, where a high sensitivity value is correctly identified. Equation 8 shows the formula for sensitivity.

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

The precision answer to the question of how often the prediction is correct when it predicts a positive value. Equation 9shows the formula for precision.

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

To evaluate and compare the type of errors each model carries; the researcher has created the confusion matrix of testing models for the classification model. The result is shown in Table 6.2.

Table 6.2 Confusion Matrix for Each Classification Model

Model	Confusion Matrix
KNN	$\begin{bmatrix} 12 & 1 \\ 1 & 4 \end{bmatrix}$

The researchers evaluate the accuracy, sensitivity, and precision score for each model based on the confusion matrix. The results are shown in Table 6.3.

Table 6.3 Predictor Values for Each Model

Model	Accuracy	Sensitivity	Precision
KNN	82.5%	75%	75%

6.4.2 Graphical Validation

The main objective of using the graphical model validation was to compare the predicted output value with the actual output quantity from the test dataset's independent variables as an input in the model vs. the previously fragmented outcome variable in the test dataset. Table 6.4 shows the result of the questionnaire responses sorted based on the type of the THU. Each cell represents the sum of the value of responses for each column. The last row demonstrates the difference of values between the responses for each feature based on the label.

Table 6.4 Feature Response Based on Label

	Shipping	Environmental Impact	Community Characteristics	Labor Workforce Dependency	Vulnerable Population	Logistic	Construction Cost	Living Condition
Off-site	25.53	7.79	6.64	9.78	6.54	27.14	14.59	8.07
On-site	9.44	6.81	13.7	6.35	13.64	7.63	9.49	9.10
Difference	16.09	0.98	7.06	3.43	7.1	19.51	5.1	1.03

The KNN model has labeled the data points based on their features in the space. In order to show how the KNN in the model operates, the researchers have depicted the KNN modeling for the test datasets on a 2D scatterplot, where each axis represents one of the features in the model. Based on values in Table 6.4, the researcher selected sets of features in pair of two. The features with the min and max value in each label was selected. In addition, values that have the highest and lowest amount in the "Difference" row were also selected. This would better show how the KNN model separates the type of THU and classifies the output based on the features. For example, the "Shipping," "Logistic," Environmental Impact," "Vulnerable Population," and "Living Condition" features have been selected. Different permutations of two from these features were used for creating different 2D KNN scatterplots. The result of these plots is shown in Figure 6.4. The color represents the different class types, which are the different types of THU. As shown in Figure 6.4, the KNN model has divided the two-dimensional space into two distinct boundaries, based on their features, to define the class labels. Each data point is colored with its specific class label, and it is positioned one of the irregular shaped spaces. The visualization shows that many data points are in the matching space in terms of the predicted class. This shows that the model has a high accuracy rate in predicting the values in their correct category or true positive values.

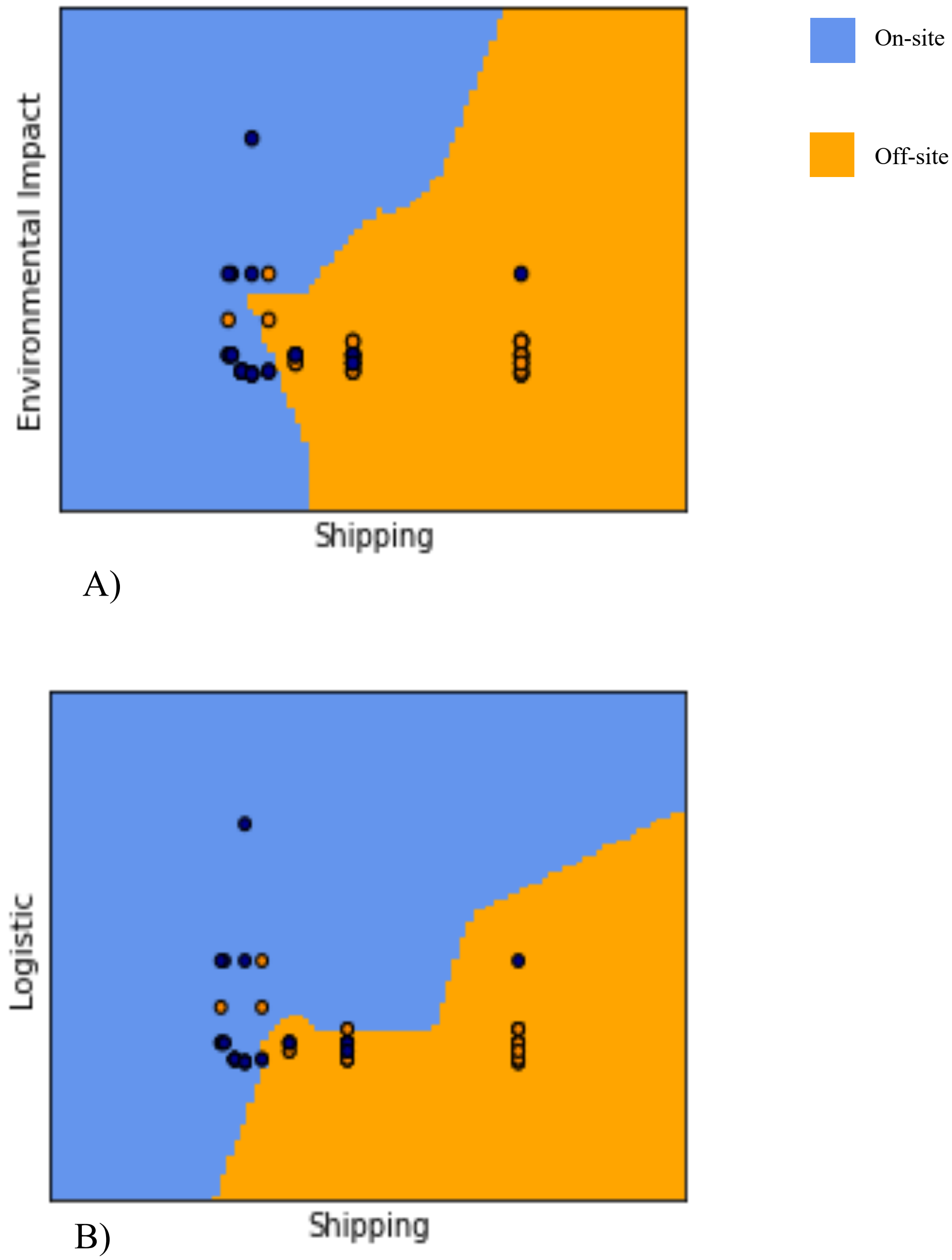
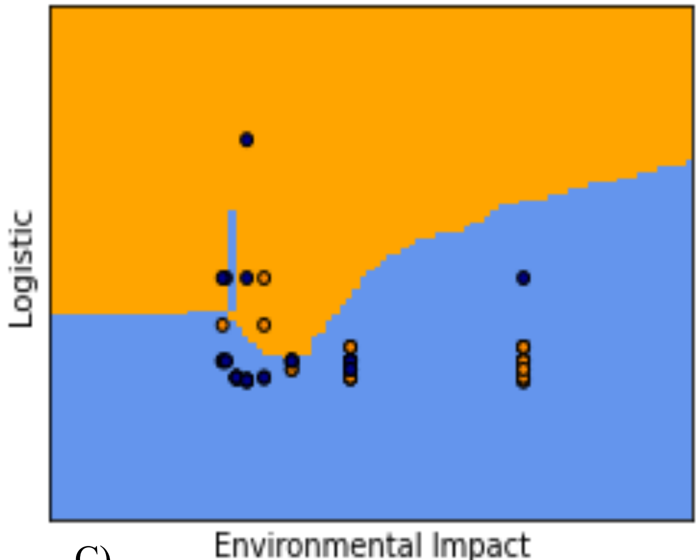


Figure 6.4 KNN Model Visualization

Figure 6.4 Continued



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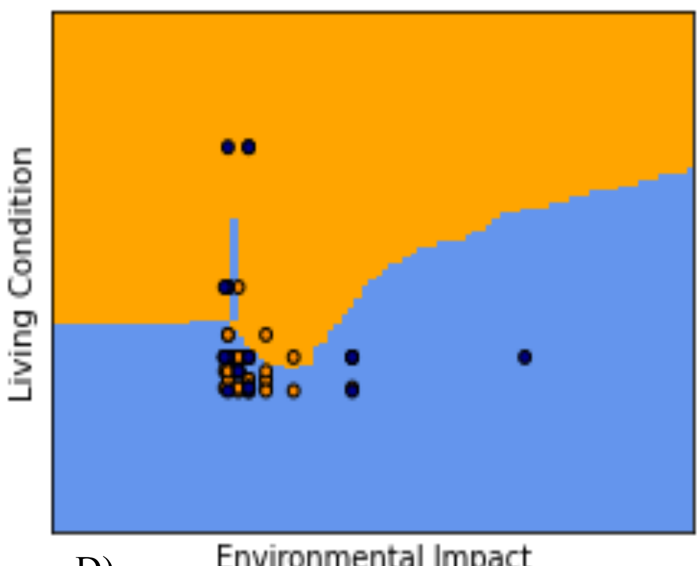
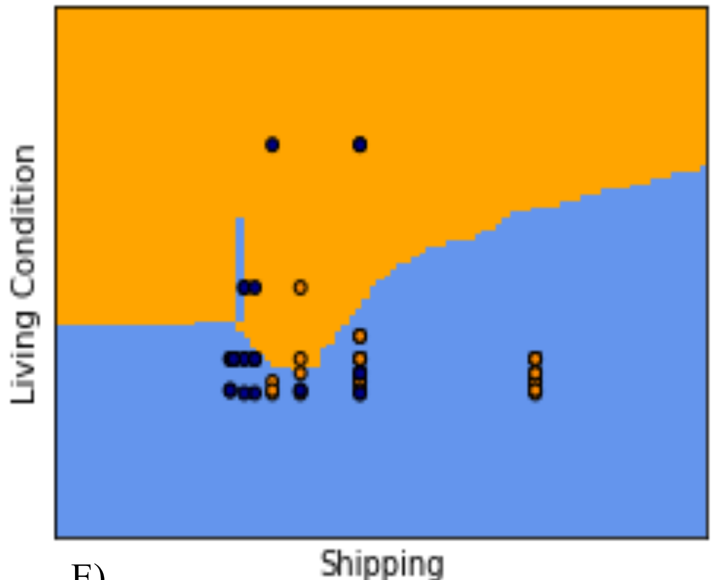


D)

Figure 6.4 Continued



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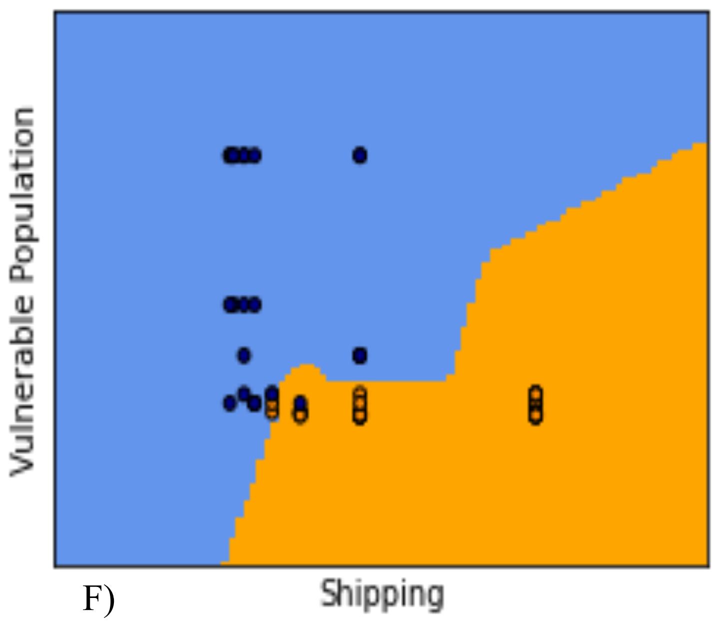


F)

Depending on the features, the type of the model classification is different. For example, in Figure 6.4-D, there is a high density of data points near the labels' separating border. This stems from the fact that the corresponding features in this figure, “Living Condition” and “Environmental Impact,” have the smallest difference value in Table 6.4. Thus, the threshold that separates the THU type in this scenario will have lots of data from both classes. In contrast, data points in Figure 6.4-F are well separated in their 2D space, and there is no dense area near the threshold. The reason for that is that the corresponding axis values in Figure 6.4-F are “Shipping” and “Vulnerable Population.” The factors with the highest values in Table 6.4, one for the “on-site” and the other for the “off-site “group.

6.5 Summary

An assimilated AHP/KNN supervised classification model was developed in order to guide the policymakers’ estimates and administrations’ judgments related to choosing the correct type of THU based on their priorities. The eight model input factors included “Shipping,” Environmental Impact,” Community Characteristics,” Labor Workforce Dependency,” Vulnerable Population,” “Site Planning,” “Cost Balance,” and “Living Condition.” The output was the type of the THU used in the affected region. These elements were used to forecast the critical condition rating process. The developed model's accuracy was verified by using the train/test split method, which produced an average validity of 82.5%. The researcher used the confusion matrix to describe a classification model's performance with a precision score and validity of 75% in the next step. These values indicated that the KNN model is robust in its prediction and performance of selecting the THU type in post-disaster circumstances and thus the industry can it from the model.

Results stated that in addition to factors such as “Logistics,” social factors such as “Vulnerable population” and “Community Characteristics” has a huge significance in the model. This shows how subjective the THU is and outlines the importance of a local approach strategy to the THU issue.

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary and Conclusions

This study aims to create a decision-making system to assist in choosing the most suitable and effective type of post-disaster temporary houses for each incident. This process can be achieved by optimizing the factors that affect building the temporary houses. The conducted research presented a methodology that addresses the challenges in prioritizing and managing the factors and subfactors affecting the THU selection. It creates a combination of AI and a multi-criteria decision-making model via deterministic data that can support the decision-making system for creating temporary structures in post-disaster situations. The developed model covers a broad range of issues, including the physical, environmental, and social factors. This tool can be used to improve the decision-making outcome of policymakers in creating the THU for affected people.

AHP and KNN modeling were the two modeling methods that were employed to help in selecting the correct type of THU for affected people. The temporary housing construction criteria consists of eight main factors: Shipping, Environmental Impact, Community Characteristics, Labor Workforce Dependency, Vulnerable Population, Site Planning, Cost Balance, and Living Condition. Each of these factors were then broken down into several subfactors.

The first approach used AHP to weigh the importance of each PI's subfactors. For each PI, the subfactors were shortlisted into two to three subfactors with the highest weight value based on the threshold filter according to their weight value. The outcome is a validated system that allows researchers and developers working in temporary housing after a disaster to recognize and analyze the factors that influence the process.

One of the salient characteristics of this result is the disparity in range and variation in variables' weight. The outcomes also show the influence of subjectivity in the current decision-making process. It also addresses how certain variables in the current method are overlooked. According to Table 5.4, there are reasonably similar Wi values for the majority of parameters in PIs. In comparison, for the subfactors in the "vulnerable population" and "community characteristics" section, there are low Wi scores. This illustrates the lack of attention given to the urban design and social factors in post-disaster housing policymakers' current strategy.

For instance, the "seniority" subfactor is considered the most impact in the "Vulnerable Population" group. However, between the first and the rest of the variables, there is a big drop in Wi. In comparison, the Wi is clustered about the same point for all variables in the "Site Planning" section, and the range of variation for subfactors in this section is negligible. The second approach was developed based on using a supervised classification model to select the post-disaster THU types most suited and optimized for each scenario. The KNN classification technique was used to develop a model that reflects the relationship

between the factors listed above and the asset risk score predictions of healthcare facilities managers. The integrated model validity was checked via mathematical, graphical, and sensitivity analysis methods. The model was able to create a well-separated threshold. The study uses qualitative, categorical information to create the model as post-disaster construction based mostly on tacit knowledge. The developed model's accuracy was verified by using the train/test split method, which produced an average validity of 82.5%. The researcher used the confusion matrix to describe a classification model's performance with a precision score and validity of 75% in the next step. These values showed that in terms of prediction, the KNN model is considered as a reliable tool and performance of selecting the THU type in post-disaster conditions and can be used in the industry.

This research shows the power of supervised classification modeling for selecting the type of temporary housing. Accordingly, the developed model can be considered an efficient tool to provide more robust, efficient decisions as an alternate to the current strategy, which relies on tacit knowledge. As the population growth tends to continue, the living pattern, especially in coastal areas, becomes more complex.

7.2 Research Contributions

This research has added to the cutting-edge decision-making tool for selecting the type of THU in post disaster situations in the following means:

- Demonstrated how machine learning techniques could help in understanding the effect of different features in post-disaster THU.
- Developed an integrated AHP/KNN THU selection model that helps post-disaster decision-makers choose the most suitable and effective type of post-disaster temporary houses for each incident.
- Created an AHP model to assess the relative weights of the main factors and subfactors involved in the THU selection model.
- Generate an AHP system to help developers working in the post-disaster temporary housing to identify and evaluate the factors affecting the process.

7.3 Model Limitations

The developed THU selection model uses AHP and KNN techniques. This model can assist in choosing the most optimized type of post-disaster temporary houses. However, the model has some limitations, including:

- The AHP/KNN THU selection model would be improved by more diversity among the expert survey respondents.
- As the subfactors are derived from the literature review and then ranked by participants, some factors are left out of the equation.
- The model is limited based on the geographic location of where the participants work in based on.
- The model took into account eight factors that help predict the type of THU. The model can benefit from the addition of more variables.
- The prototype’s output results were limited to the asset's PI ranking.

7.4 Recommendations for Future Research

While certain factors affect influencing the THU types and built, the effect and magnitude of these factors are not constant and will change based on region, population growth. This would cause problems to become more complex, and therefore imprecise knowledge will lose its functionality over time. Thus, there is a severe need for systematic data collection in the construction industry sector, especially the post-disaster temporary housing segment. This is much more important in the post-disaster construction process because of the limitations and environmental conditions, where data recording can be more difficult. There is currently no standard procedure for identifying and measuring the factors that affect the THU. Another issue in this area is the lack of a standardized approach to calculating the requirements weight. In multicriteria cases, weighing the variables contributes to a more stable result that is less vulnerable to errors. This is especially important for subjective factors like "Community Characteristics". Future research can also explore different data collection techniques and strategies to create artificial intelligent models.

In addition to numerical data, using other kinds of input data such as images and text can evaluate post-disaster scenarios. AI can help label data and recognize patterns in the input data that would help in visual search and inspection. Future research can also benefit from other AI libraries for creating models such as TensorFlow and Keras, which are mostly used for computer vision applications. It can also benefit from AI techniques such as Natural Language Processing (NLP) for analyzing text and documents. Another branch of study explores deep learning techniques such as Artificial Neural Networks (ANN) or Convolutional Neural Networks (CNN) in the application. Using deep learning would create a multi-layer algorithm environment that helps the model learn and create decisions on its own when faced with a new scenario. However, it is worth noting that using deep learning methods requires a large volume of data, both structured and unstructured, showing day-to-day information, also known as big data, as input. Therefore, there needs to be a robust platform of data collection first before applying in-depth learning strategies. There is also a need to re-evaluate policymakers' existing policies, as there is a lack of commitment to particular parameters. Future research should also consider building a rating system for the key PI values to measure and evaluate different THU performance more accurately.

APPENDIX A. INSTITUTIONAL REVIEW BOARD(IRB) APPROVAL LETTER

Date: 3-22-2020

IRB #: IRB-2020-306
Title: Decision Making for Post Disaster Temporary Housing
Creation Date: 2-18-2020
End Date:
Status: Approved
Principal Investigator: EMAD ELWAKIL
Review Board: Exempt Reviewer
Sponsor:

Study History

Submission Type	Initial	Review Type	Exempt	Decision	Exempt

Key Study Contacts

Member	Mahdi Afkhamiaghda	Role	Co-Principal Investigator	Contact	mafkhami@purdue.edu
Member	EMAD ELWAKIL	Role	Principal Investigator	Contact	eelwakil@purdue.edu
Member	EMAD ELWAKIL	Role	Primary Contact	Contact	eelwakil@purdue.edu

Figure A-1. Institutional review board (IRB) Approval letter

APPENDIX B. EXPERT SURVEY QUESTIONS

Description

Please take the time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty or loss of benefits to which you are otherwise entitled. You may ask questions from the researchers about the study whenever you would like. If you decide to take part in the study, you will be asked to sign this form, be sure you understand what you will do and any possible risks or benefits. The study is about decision-making process for the type of temporary housing in a post-disaster scenario. Researchers want to collect data through a set of questionnaires to assess the importance of different factors in the process.

Possible risks or discomforts:

The anticipated level of risk for this study is minimal.These risks are no greater than the participant would encounter in daily life or during the performance of routine physical or psychological exams or tests. Breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section."

Purpose of this study:

Participants in this study will be the state, federal, and local coordinating officers who play a role in providing temporary housing to people affected by natural disasters in the country. This research also targets all the non-governmental groups who participate in creating post-disaster temporary housing as well as vendors and manufacturing companies who create these temporary housing units.
The purpose of this study is to develop a framework that can assist contractors in creating temporary housing in post-disaster situations and help them with the decision-making by optimizing different aspects of the process. The information about you and your participation will be kept confidential:

Figure B-1. Survey Question Description

Section1: Demographic Data

Select your highest completed level of education

- University Graduate
- Some College
- High School
- Less than High School

What is the scope of work of your organization?

- Municipal
- State
- Federal

What is the type of your organization?

- Private Sector
- Governmental

Figure B-2. Survey Demographic Question Part 1

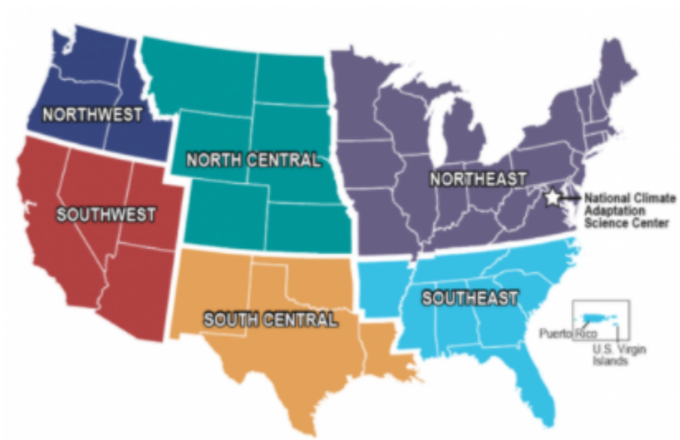
What is your role in the organization?

- Top Management
- Middle Management
- First-level Supervisor
- Staff
- Operational Worker

How many years of experience do you have in your current industry?

- Less than 1
- 1-2
- 3-5
- 6-10
- Over 10

Figure B-3. Survey Demographic Question Part 2



Base on the figure above, please specify the current demographic region of your organization:

- Northeast
- Southeast
- North Central
- South Central
- Northwest
- Southwest

Figure B-4. Survey Demographic Question Part 3

Section2: Questions

1. **Temporary House Types**

Please rate the importance or usage of the following type of temporary house from 1 = not at all, 2 = seldom, 3 = Occasionally, 4 = Often, 5 = always.

Note: Please see figure below for a reference on type of the temporary houses.

	1	2	3	4	5
Steel-framed	○	○	○	○	○
Timber-framed	○	○	○	○	○
Superadobe	○	○	○	○	○
Bamboo	○	○	○	○	○
Panelized Homes	○	○	○	○	○
FEMA Trailers	○	○	○	○	○
3D Printed	○	○	○	○	○
Containers	○	○	○	○	○
Manufactured Homes	○	○	○	○	○
Prefabricated Modular	○	○	○	○	○

If there are any other types of temporary houses that are used, please specify them below:

Figure B-5. Survey Question Part 1

2. **Decision-Making Factors Identification and Assessment**

From the list provided, please evaluate each factor based on their importance from 1 = not important at all, 2 = slightly important, 3 = important, 4 = fairly important, 5 = most important.

Shipping

	1	2	3	4	5
Transportation	○	○	○	○	○
Resource Availability	○	○	○	○	○
Time	○	○	○	○	○
Vehicle Availability	○	○	○	○	○
Road Condition	○	○	○	○	○
Traffic	○	○	○	○	○

Environmental Impact

	1	2	3	4	5
Material's Durability	○	○	○	○	○
Material's Life Cycle	○	○	○	○	○
Material's Recycle-ability	○	○	○	○	○
Site Pollution through Construction	○	○	○	○	○
Material's Transportation	○	○	○	○	○

Figure B-6. Survey Subfactors Question Part 1

Community Characteristics

	1	2	3	4	5
Climate					
Units being Customizable					
Privacy					
Safety					
Population Density					
Cultural Appropiateness					
Aesthetics					

Labor Workforce Dependency

	1	2	3	4	5
Installation Methods and Equipment					
Speed					
Safety					
Workforce Trainig					
Psychology					
Working Hours					
Weather Condition					

Vulnerable Population

	1	2	3	4	5
Seniority					
Ethnicity					
Minority					
Mental Illness					
Poverty					
Illness					

Figure B-7. Survey Subfactors Question Part 2

Logistic

	1	2	3	4	5
Land Availability	○	○	○	○	○
Number of Evacuees	○	○	○	○	○
City Density	○	○	○	○	○
Accessibility	○	○	○	○	○

Construction Cost

	1	2	3	4	5
Shipping Cost	○	○	○	○	○
Labor Cost	○	○	○	○	○
Material Cost	○	○	○	○	○

Living Condition

	1	2	3	4	5
Health Risk	○	○	○	○	○
Thermal Insulation	○	○	○	○	○
Air Quality	○	○	○	○	○
Material Quality	○	○	○	○	○
Structural Quality	○	○	○	○	○

Figure B-8. Survey Subfactors Question Part 3

Please rank the following factors in the order of importance -most important item at the top-, in the process of choosing the type of temporary house for a region by dragging each factor.

1. Shipping
2. Environmental Impact
3. Community Characteristics
4. Labor Workforce Dependency
5. Vulnerable Population
6. Logistic
7. Construction Cost
8. Living Condition

Figure B-9. Survey Ranking Question

APPENDIX C. DESCRIPTIVE ANALYSIS OF SUBFACTORS IN SURVEY QUESTIONS

Table C-1 Subfactor Descriptive Analysis - Shipping

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Transportation	90	4.4	0.871191	1	4	5	5	5	5
Resource Availability	90	4.075	0.729858	3	4	4	5	5	4
Time	90	3.125	1.202295	1	2	3	4	5	2
Vehicle Availability	90	3.3	0.882886	1	3	3	4	5	3
Road Condition	90	2.85	0.83359	1	2	3	3	5	3
Traffic	90	2.25	1.103607	1	1	2	3	5	2

Table C-2 Subfactor Descriptive Analysis – Environmental Impact

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Material's Durability	90	3.7	1.136797	1	3	4	5	5	5
Material's Life Cycle	90	3.45	1.108244	2	2.75	3	4	5	3
Material's Recyclability	90	2.775	0.919518	1	2	3	3	5	2
Site Pollution through Construction	90	2.8	0.992278	1	2	2.5	4	5	2
Material's Transportation	90	3.45	1.011473	1	3	3.5	4	5	4

Table C-3 Subfactor Descriptive Analysis – Community Characteristics

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Climate	90	3.875	0.607116	2	4	4	4	5	4
Units being Customizable	90	2.575	0.957762	1	2	2	3	5	2
Privacy	90	3.975	1.120611	1	3	4	5	5	5
Safety	90	4.55	0.749359	2	4	5	5	5	5
Population Density	90	3.435897	0.852083	2	3	3	4	5	3
Cultural Appropriateness	90	2.3	1.136797	1	1.75	2	3	5	2

Table C-4 Subfactor Descriptive Analysis – Labor Workforce Dependency

Subfactor	`Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Installation Methods and Equipment	90	3.5	0.784465	1	3	3	4	5	3
Speed	90	4.325	0.944281	1	4	5	5	5	5
Safety	90	4.125	1.042372	1	3.75	4	5	5	5
Workforce Training	90	3.5	0.9337	2	3	4	4	5	4
Psychology	90	2.05	1.036513	1	1	2	2.25	5	2
Working Hours	90	2.65	0.735544	1	2	3	3	4	3
Weather Condition	90	3.225	0.946993	1	3	3	4	5	3

Table C-5 Subfactor Descriptive Analysis – Vulnerable Population

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Seniority	90	3.975	0.76753	2	3.75	4	4.25	5	4
Ethnicity	90	2.325	0.997111	1	2	2	3	5	2
Minority	90	2.275	1.012423	1	2	2	3	5	2
Mental Illness	90	2.625	1.078639	1	2	2.5	3.25	5	2
Poverty	90	2.65	1.210001	1	2	2	3.25	5	2

Illness	90	3.075	1.118321	1	2	3	4	5	4

Table C-6 Subfactor Descriptive Analysis – Logistic

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Land Availability	90	4.35	0.892993	2	4	5	5	5	5
Number of Evacuees	90	4.25	0.669864	3	4	4	5	5	4
City Density	90	3.525	0.816104	2	3	4	4	5	4
Accessibility	90	3.45	0.875595	2	3	3.5	4	5	4

Table C-7 Subfactor Descriptive Analysis – Construction Cost

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Shipping Cost	90	4.1	0.841244	2	4	4	5	5	4
Labor Cost	90	3.175	0.873763	2	3	3	4	5	3
Material Cost	90	3.85	0.892993	2	3	4	5	5	4

Table C-8 Subfactor Descriptive Analysis – Living Condition

Subfactor	Count	Mean	Std	Min	25%	50%	75%	Max	Mode
Health Risk	90	4.1	0.744208	2	4	4	5	5	4
Thermal Insulation	90	3.05	0.985797	1	2	3	4	5	3
Air Quality	90	3.4	0.744208	2	3	3	4	5	3
Material Quality	90	3.625	0.867874	2	3	4	4	5	4
Structural Quality	90	3.95	0.875595	2	3.75	4	5	5	4

APPENDIX D. EXCEL-BASED PRIORITY ASSIGNMENT THROUGH AHP

Table D-1. Pairwise Comparison Matrix for the “Shipping” Performance Indicator

Factors	SH-1	SH-2	SH-3	SH-4	SH-5	SH-6
SH-1	1	1.075	1.433333	1.330077	1.535714	1.954545
SH-2	0.930233	1	1.333333	1.237281	1.428571	1.818182
SH-3	0.697674	0.75	1	0.927961	1.071429	1.363636
SH-4	0.751836	0.808224	1.077632	1	1.154605	1.469498
SH-5	0.651163	0.7	0.933333	0.866097	1	1.272727
SH-6	0.511628	0.55	0.733333	0.680505	0.785714	1

Table D-2. Square Matrix of the “Shipping” Pairwise Comparison

Factors	SH-1	SH-2	SH-3	SH-4	SH-5	SH-6
SH-1	5.999999498	6.449999453	8.599997416	7.980463132	9.214283293	11.72727029
SH-2	5.581395564	6.000000224	7.999998573	7.423687541	8.571427365	10.90908998
SH-3	4.186046518	4.500000001	5.999998707	5.56776545	6.428570286	8.181817179
SH-4	4.511016843	4.8493431	6.465789405	6.000001102	6.927631767	8.816986371
SH-5	3.906976941	4.200000207	5.599999068	5.196581341	5.999999227	7.636363074
SH-6	3.06976756	3.300000123	4.399999215	4.083028148	4.714285051	5.999999487

Table D-3. Normalized Critreia Weight for the “Shipping” subfactors

Criteria Weight	Normalized
49.97201308	0.220141436
46.48559924	0.204782756
34.86419814	0.153587061
37.57076859	0.165510301
32.53991986	0.143347931
25.56707958	0.112630516
226.9995785	

Table D-4. Pairwise Comparison Matrix for the "Environmental Impact" Performance Indicator

Factors	EI-1	EI-2	EI-3	EI-4	EI-5
EI-1	1	1.074074	1.342593	1.342593	1.08209
EI-2	0.931034	1	1.25	1.25	1.007463
EI-3	0.744828	0.8	1	1	0.80597
EI-4	0.744828	0.8	1	1	0.80597
EI-5	0.924138	0.992593	1.240741	1.240741	1

Table D-5. Square Matrix of the "Environmental Impact" Pairwise Comparison

Factors	EI-1	EI-2	EI-3	EI-4	EI-5
EI-1	5.000001619	5.370371759	6.712964929	6.712964929	5.410449175
EI-2	4.655172842	5.000000134	6.250000381	6.250000381	5.037313581
EI-3	3.724138704	4.000000569	5.000000883	5.000000883	4.029851331
EI-4	3.724138704	4.000000569	5.000000883	5.000000883	4.029851331
EI-5	4.620691106	4.962964198	6.20370546	6.20370546	5.000001258

Table D-6. Normalized Critreia Weight for the "Environmental Impact" subfactors

Criteria Weight	Normalized
29.20675241	0.230158751
27.19248732	0.214285684
21.75399237	0.171428567
21.75399237	0.171428567
26.99106748	0.21269843
126.898292	

Table D-7. Pairwise Comparison Matrix for the "Community Characteristics" Performance Indicator

Factors	CC-1	CC-2	CC-3	CC-4	CC-5	CC-6	CC-7
CC-1	1	1.525253	0.967949	0.843575	1.123116	1.696629	2.287879
CC-2	0.655629	1	0.634615	0.553073	0.736348	1.11236	1.5
CC-3	1.033113	1.575758	1	0.871508	1.160305	1.752809	2.363636
CC-4	1.18543	1.808081	1.147436	1	1.331376	2.011236	2.712121
CC-5	0.89038	1.358054	0.861842	0.751103	1	1.510645	2.037081
CC-6	0.589404	0.89899	0.570513	0.497207	0.661969	1	1.348485
CC-7	0.437086	0.666667	0.423077	0.368715	0.490898	0.741573	1

Table D-8. Square Matrix of the "Community Characteristics" Pairwise Comparison

Factors	CC-1	CC-2	CC-3	CC-4	CC-5	CC-6	CC-7
CC-1	6.99999973	10.67676942	6.77564118	5.905028467	7.861811598	11.87640542	16.0151511
CC-2	4.589404299	7.000001908	4.442308279	3.871509153	5.154433333	7.786518311	10.5000008
CC-3	7.231787577	11.03030449	6.999999943	6.100559022	8.122136233	12.26966349	16.5454536
CC-4	8.298012612	12.65656724	8.032051162	7.000000369	9.319630614	14.07865225	18.9848472
CC-5	6.232659581	9.506381683	6.032895221	5.257719096	6.999999609	10.57451355	14.2595698
CC-6	4.125828279	6.292931271	3.993590438	3.480447768	4.633783694	7.000001601	9.43939511
CC-7	3.059602243	4.66666699	2.961538251	2.581005577	3.43628819	5.191011151	6.99999915

Table D-9. Normalized Critreia Weight for the "Community Characteristics" subfactors

Criteria Weight	Normalized
66.11080691	0.172680487
43.34417616	0.113214371
68.29990436	0.178398379
78.36976152	0.204700702
58.86373857	0.153751248
38.96597817	0.101778581
28.89611156	0.075476232
382.8504772	

Table D-10. Pairwise Comparison Matrix for the “Labor Workforce Dependency” Performance Indicator

Factors	LW-1	LW-2	LW-3	LW-4	LW-5	LW-6	LW-7
LW-1	1	0.805882	0.845679	1.014815	1.75641	1.334872	1.07651
LW-2	1.240876	1	1.049383	1.259259	2.179487	1.65641	1.335815
LW-3	1.182482	0.952941	1	1.2	2.076923	1.578462	1.272953
LW-4	0.985401	0.794118	0.833333	1	1.730769	1.315385	1.060794
LW-5	0.569343	0.458824	0.481481	0.577778	1	0.76	0.612903
LW-6	0.749136	0.603715	0.633528	0.760234	1.315789	1	0.806452
LW-7	0.928928	0.748607	0.785575	0.94269	1.631579	1.24	1

Table D-11. Square Matrix of the “Labor Workforce Dependency” Pairwise Comparison

Factors	LW-1	LW-2	LW-3	LW-4	LW-5	LW-6	LW-7
LW-1	7.00000023	5.64117728	5.9197518	7.10370431	12.2948708	9.3441035	7.53556769
LW-2	8.68613157	7.00000092	7.3456774	8.81481546	15.2564089	11.594872	9.35070433
LW-3	8.27737278	6.67058939	6.9999987	8.40000096	14.5384608	11.049232	8.91067155
LW-4	6.89780996	5.55882393	5.8333317	7.00000010	12.1153828	9.2076926	7.42555888
LW-5	3.98540144	3.21176504	3.3703695	4.04444463	6.9999992	5.3200003	4.29032305
LW-6	5.24394935	4.226006712	4.4346968	5.32163777	9.210525418	7.0000006	5.64516200
LW-7	6.50249714	5.240248281	5.4990240	6.59883078	11.42105143	8.6800007	7.00000083

Table D-12. Normalized Critreia Weight for the “Labor Workforce Dependency” subfactors

Criteria Weight	Normalized
54.83917585	0.150236641
68.04861154	0.186425027
64.84632662	0.177652092
54.03860011	0.148043395
31.22230332	0.085536187
41.08197874	0.112547616
50.94165324	0.139559043
365.0186494	

Table D-13. Pairwise Comparison Matrix for the "Vulnerable Population" Performance Indicator

Factors	VP-1	VP-2	VP-3	VP-4	VP-5	VP-6
VP-1	1	1.733333	1.793103	1.544554	1.529412	1.3
VP-2	0.576923	1	1.034483	0.891089	0.882353	0.75
VP-3	0.557692	0.966667	1	0.861386	0.852941	0.725
VP-4	0.647436	1.122222	1.16092	1	0.990196	0.841667
VP-5	0.653846	1.133333	1.172414	1.009901	1	0.85
VP-6	0.769231	1.333333	1.37931	1.188119	1.176471	1

Table D-14. Square Matrix of the "Vulnerable Population" Pairwise Comparison

Factors	VP-1	VP-2	VP-3	VP-4	VP-5	VP-6
VP-1	5.999998955	10.39999797	10.75862019	9.267325199	9.176470131	7.799999757
VP-2	3.461538221	5.999999455	6.206896914	5.346534328	5.294117937	4.50000033
VP-3	3.346153268	5.799998874	5.999999731	5.168315984	5.117646811	4.34999987
VP-4	3.884615521	6.733333427	6.965518378	6.000000263	5.941177419	5.0500009
VP-5	3.923076397	6.799998943	7.034482715	6.05940518	5.999999941	5.100000045
VP-6	4.615384497	7.999999625	8.275862916	7.128712751	7.058824227	6.000000704

Table D-15. Normalized Critreia Weight for the "Vulnerable Population" subfactors

Criteria Weight	Normalized
53.4024122	0.237804859
30.80908719	0.137195125
29.78211454	0.132621941
34.57464591	0.153963435
34.91696322	0.155487799
41.07878472	0.182926842
224.5640078	

Table D-16. Pairwise Comparison Matrix for the "Site Planning" Performance Indicator

Factors	LO-1	LO-2	LO-3	LO-4
LO-1	1	1.024096	1.231884	1.268657
LO-2	0.976471	1	1.202899	1.238806
LO-3	0.811765	0.831325	1	1.029851
LO-4	0.788235	0.807229	0.971014	1

Table D-17. Square Matrix of the "Site Planning" Pairwise Comparison

Factors	LO-1	LO-2	LO-3	LO-4
LO-1	4.000000211	4.096384688	4.927535763	5.074627239
LO-2	3.905883554	4.000000185	4.811594971	4.955225507
LO-3	3.247059357	3.325300882	4.000000065	4.119403748
LO-4	3.152940889	3.228914524	3.884057042	3.999999718

Table D-18. Normalized Critreia Weight for the "Site Planning" subfactors

Criteria Weight	Normalized
18.0985479	0.279605245
17.67270422	0.273026368
14.69176405	0.226973695
14.26591217	0.220394691
64.72892834	

Table D-19. Pairwise Comparison Matrix for the "Construction Cost" Performance Indicator

Factors	CO-1	CO-2	CO-3
CO-1	1	1.290323	1.066667
CO-2	0.775	1	0.826667
CO-3	0.9375	1.209677	1

Table D-20. Square Matrix of the "Construction Cost" Pairwise Comparison

Factors	CO-1	CO-2	CO-3
CO-1	3.000000638	3.870968537	3.200001443
CO-2	2.325000313	3.000000382	2.480000925
CO-3	2.812499675	3.629031813	3.000000369

Table D-21. Normalized Critreia Weight for the "Construction Cost" subfactors

Criteria Weight	Normalized
10.07097062	0.368663644
7.805001619	0.285714302
9.441531857	0.345622053
27.31750409	

Table D-22. Pairwise Comparison Matrix for the "Living Condition" Performance Indicator

Factors	LC-1	LC-2	LC-3	LC-4	LC-5
LC-1	1	1.355932	1.203008	1.121564	1.032433
LC-2	0.7375	1	0.887218	0.827154	0.76142
LC-3	0.83125	1.127119	1	0.9323	0.85821
LC-4	0.891612	1.208965	1.072616	1	0.92053
LC-5	0.968586	1.313336	1.165216	1.086331	1

Table D-23. Square Matrix of the "Living Condition" Pairwise Comparison

`Factors	LC-1	LC-2	LC-3	LC-4	LC-5
LC-1	5.000000321	6.779660222	6.015038219	5.607820909	5.162166548
LC-2	3.687501147	5.000000648	4.436091782	4.135768941	3.807098769
LC-3	4.156250321	5.635592633	5.000000585	4.661501192	4.291050999
LC-4	4.458060208	6.044826304	5.363080163	5.000000329	4.60264956
LC-5	4.842928856	6.566682002	5.826080058	5.431655191	5.000000746

Table D-24. Normalized Critreia Weight for the "Living Condition" subfactors

Criteria Weight	Normalized
28.56468622	0.225787258
21.06646129	0.166518144
23.74439573	0.187685661
25.46861656	0.201314625
27.66734685	0.218694312
126.5115067	

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