Optimized Emergency Shelter Ranking: A Multi-Criteria Decision-Making Framework for Post-Disaster Response

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Abstract

This thesis introduces a comprehensive multi-criteria decision-making (MCDM) framework designed to optimize the selection and prioritization of emergency shelters during natural disasters. Recognizing that effective shelter planning must extend beyond the basic objective of survival, this study emphasizes the importance of accommodating the nuanced and diverse needs of displaced populations, particularly refugees and vulnerable groups. To capture these needs accurately, a set of detailed evaluation criteria was developed in direct collaboration with the Emergency Management Organization (EMO) of Manitoba, Canada. This collaboration ensured that the model reflects not only theoretical soundness but also practical considerations rooted in field experience and operational constraints.

The core of the proposed methodology is an enhanced version of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a widely used MCDM method. To address a major limitation of traditional TOPSIS—its sensitivity to the subjectivity of weight assignment—the model incorporates a hybrid entropy-based weighting mechanism. Specifically, it combines Shannon entropy and Wen entropy to compute objective and context-sensitive weights for each criterion. Shannon entropy captures the variability in continuous data, while Wen entropy adjusts for the significance of binary criteria. This dual entropy approach results in a more balanced and unbiased evaluation process, allowing the model to handle diverse data types with improved precision and interpretability.

The model is applied to a real-world case study in Manitoba, where hotels are evaluated as potential shelters. Unlike previous studies that focus on hypothetical sites or vacant land, this research deliberately evaluates existing, operational infrastructure to enhance the model's deployability. The selected shelters are assessed across both quantitative factors (e.g., proximity to hospitals, capacity, structural safety) and qualitative or binary indicators (e.g., pet-friendliness, accessibility, age-specific amenities). The model also introduces a tunable φ parameter that enables decision-makers to simulate varying disaster scenarios by shifting the relative importance of binary versus continuous data. This allows emergency planners to account for the evolving nature of crisis conditions, such as weather changes, population demographics, or transportation limitations.

A detailed sensitivity analysis, along with stability metrics such as standard deviation and rank change (RC), was conducted to validate the robustness of the shelter rankings across different weighting schemes. The findings highlight key facilities that consistently perform well across all scenarios, as well as context-specific shelters that may be optimal in certain emergencies. These results provide actionable insights for emergency managers, enabling data-driven decisions that can reduce response times, minimize population displacement, and prevent repeated relocations during prolonged crises.

Beyond methodological innovation, this research contributes to disaster preparedness and policy planning by creating a decision-support tool that is grounded in operational reality and informed by human-centered priorities. By aligning academic modeling with field-based expertise and real infrastructure, the study bridges the gap between theory and practice. Moreover, its focus on the Canadian urban context fills an important gap in the global literature, offering a replicable framework for other regions facing similar challenges. Ultimately, this work enhances the resilience and efficiency of emergency response systems, ensuring that shelter planning is not only mathematically sound but also socially responsible and practically viable.

Acknowledgement

I would like to express my deepest gratitude to my advisor, Professor Narendra Malalgoda, for his unwavering support, insightful feedback, and guidance throughout the development of this thesis. His expertise and encouragement have been invaluable in shaping my research and bringing this work to fruition. I am also sincerely thankful to my co-advisor Professor Gajpal and my committee members, Professor Divya Ramachandran and Professor Srimantoorao Appadoo, for their thoughtful advice and contributions.

Their insightful suggestions and constructive critiques have been instrumental in enhancing the quality of this research.

Chapter 1

Introduction

Natural disasters, including floods, tornadoes, and other hazards, pose serious threats to urban populations and infrastructure, requiring carefully coordinated emergency response systems. These hazards are a growing concern globally, threatening the safety, livelihoods, and infrastructure of urban areas.

Globally, natural hazards occur with varying frequency, with significant trends observed over time. According to Statista (2023), 398 natural disaster events were recorded worldwide, reflecting a consistent level from the previous year. These hazards are geographically dispersed, with regions like Europe, the Middle East, and Africa experiencing the highest incidence. Such data underscores the importance of understanding global patterns to mitigate localized impacts.

Flooding is Canada's most frequent and costly natural hazard, occurring due to various climatic and environmental factors (Get Prepared, n.d.-a). This phenomenon can occur throughout the year, triggered by factors such as heavy rainfall, melting snow, ice jams, and coastal storm surges. Flooding's widespread nature and destructive potential make it a critical focus for disaster preparedness efforts nationwide.

Manitoba, in particular, faces unique vulnerabilities to natural hazards due to its geography and climate (Get Prepared, n.d.-b). The province is significantly impacted by river flooding, which poses substantial risks to communities and infrastructure. Additionally, thunderstorms and tornadoes can occur widely, and all regions of Manitoba are susceptible to wildfires. This combination of natural hazards emphasizes the importance of tailored emergency management and preparedness in the region.

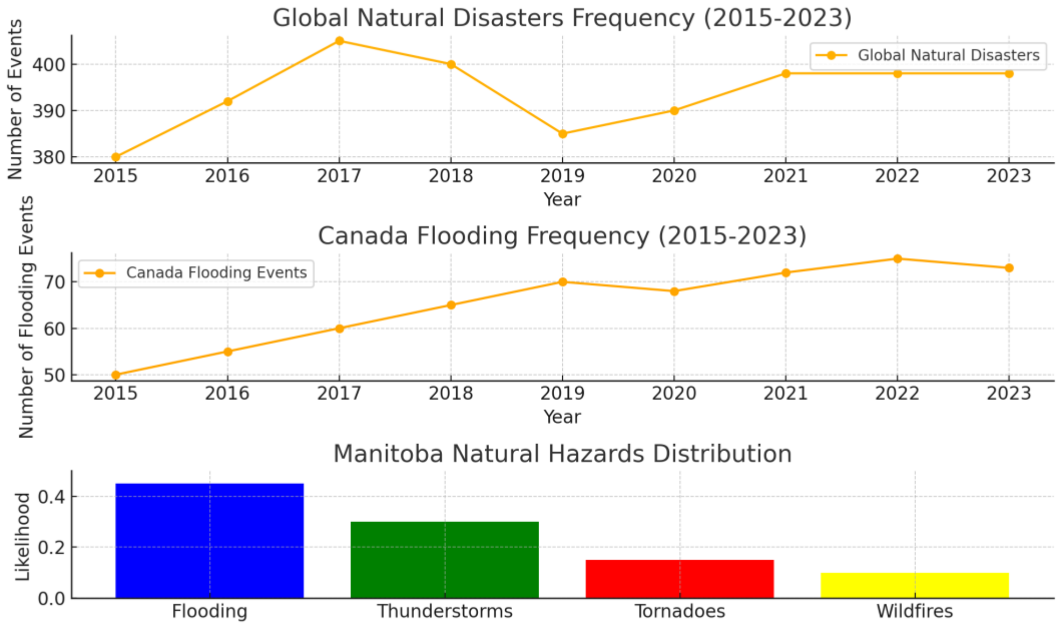

Figure 2: Frequency and Distribution of Natural Hazards: A Global, National, and Provincial Perspective.

Global Natural Disasters Frequency figure shows a trend analysis of the frequency of natural disaster events worldwide, highlighting the consistency of occurrences between 2015 and 2023. Canada Flooding Frequency figure shows an illustration of the increasing frequency of flooding events in Canada, emphasizing its role as the most frequent and costly natural hazard in the country. Manitoba Natural Hazards Distribution figure shows a distribution chart showing the likelihood of various natural hazards in Manitoba, with flooding as the most prevalent risk, followed by thunderstorms, tornadoes, and wildfires.

The increasing frequency and intensity of these disasters, attributed to climate change and urban expansion, call for a more structured and scientific approach to disaster preparedness and response. One of the most critical components in disaster management is the strategic selection and ranking of emergency shelters. These shelters are not only vital for providing immediate safety to refugees but also play a key role in streamlining resource allocation and minimizing disaster impacts on vulnerable populations.

The complexity of urban environments exacerbates the challenge of selecting optimal shelter locations. Urban centers are characterized by high population densities, intricate transportation networks, and diverse socio-economic conditions. Effective shelter ranking must consider multiple, sometimes conflicting, criteria such as safety, accessibility, proximity to critical infrastructure, and capacity. The consequences of poor shelter placement can be dreadful, leading to overcrowding, delayed evacuation, and inequitable resource distribution.

One of the most critical components of disaster management is the strategic allocation and ranking of shelters to support efficient evacuations and minimize risks to human life. In recent years, increased frequency and severity of natural hazards have highlighted the need for improved methodologies to assess and prioritize emergency shelter locations. Effective shelter site selection not only ensures safety and accessibility for evacuees but also facilitates rapid deployment of resources and improves overall emergency response efficiency. The current research addresses this need by focusing on optimizing shelter rankings for effective evacuation planning in disaster-prone urban areas.

1.1 Background and Problem Statement

When a natural hazard impacts a region, emergency management agencies must make swift, informed decisions about where to direct evacuees for safety. These decisions are particularly crucial in areas with densely populated urban environments, where the efficiency of emergency shelters significantly impacts overall disaster response outcomes. Shelters must be ranked based on various criteria, including safety, accessibility, infrastructure support, and capacity, to determine the most effective allocation of resources during an evacuation.

In practice, achieving an optimum ranking of shelters involves complex decision-making processes. Emergency shelters are evaluated based on multiple criteria, each with different levels of significance. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is widely used in multi-criteria decision-making (MCDM) frameworks due to its straightforward implementation and ability to handle multiple alternatives. TOPSIS ranks shelters by calculating their distances from an ideal and an anti-ideal solution, providing a robust mathematical approach to determining optimal locations. However, TOPSIS has a known limitation: it lacks a specific formulation for calculating the weights of criteria, leaving weight determination as an external challenge that can significantly impact the accuracy and reliability of the model.

To address this limitation, the current research introduces an innovative solution by integrating Shannon entropy and Wen entropy methods to compute criteria weights. Shannon entropy is a well-established approach for determining weights based on the distribution of information across criteria, whereas Wen entropy further refines weight calculations by addressing variations in importance among criteria. By combining these two entropy-based methods, this study aims to enhance the accuracy and precision of the TOPSIS model, providing a more reliable framework for shelter ranking.

1.2 Research Objectives

The primary objective of this research is to develop an optimized ranking framework for emergency shelters, facilitating more effective evacuation planning in response to natural hazards. This goal involves several specific objectives:

1. To define a comprehensive set of criteria that reflect the key characteristics and requirements for effective shelter operation in the event of an evacuation.
2. To apply the TOPSIS model to rank shelters based on these criteria, enabling decision-makers to identify the most suitable locations under various disaster scenarios.
3. To address the weighting challenge within the TOPSIS model by integrating Shannon entropy and Wen entropy, thereby enhancing the model's reliability and applicability.
4. To apply the optimized TOPSIS model to a case study of Manitoba, Canada, using local hotels as potential shelters and collaborating with Emergency Management Organizations (EMO) to ensure relevance and accuracy in criteria selection.

1.3 Scope and Methodology

The scope of this research focuses on the province of Manitoba, Canada, which is vulnerable to several types of natural hazards, including floods and tornadoes. Given the logistical and practical considerations of emergency planning, local hotels have been selected as alternative shelter options. This selection allows for the application of the TOPSIS model to evaluate and rank hotels based on their suitability as emergency shelters.

Criteria for shelter selection have been developed in collaboration with Manitoba's Emergency Management Organization (EMO). These criteria include a range of factors essential to shelter functionality, such as accessibility, proximity to critical infrastructure, safety measures, capacity, and operational feasibility. The TOPSIS model will then use these criteria to calculate an optimized ranking of hotels, facilitating a data-driven approach to shelter selection and allocation.

To overcome the weight calculation limitation in TOPSIS, this study employs a combination of Shannon entropy and Wen entropy methodologies. Shannon entropy allows for an objective assessment of each criterion's weight based on data variability, while Wen entropy adjusts these weights based on relative significance. The integration of these entropy-based techniques enhances the model's ability to reflect nuanced differences among criteria, resulting in more precise shelter rankings. This hybrid approach allows the TOPSIS model to produce a ranking that is both practical and adaptable to a range of disaster response scenarios.

1.4 Significance of the Study

This research contributes to the field of disaster management by providing a robust and flexible model for shelter ranking that can be applied to various urban contexts. By addressing the limitations in the traditional TOPSIS model, the study provides a more accurate and reliable method for emergency shelter selection. The integration of entropy-based weighting techniques enhances the precision of shelter rankings, enabling emergency management agencies to make better-informed decisions during critical situations.

The case study in Manitoba serves as a practical application, demonstrating the model's utility in a real-world context. This case study not only validates the model's effectiveness but also provides insights that can guide policy decisions and disaster preparedness efforts across Canada and similar regions worldwide. The collaboration with EMO ensures that the model's criteria align with on-the-ground realities, making the findings applicable to actual disaster response and evacuation planning.

Chapter 2

Literature Review

Effective disaster management relies heavily on strategic infrastructure planning, particularly regarding the optimal placement of relief centers and emergency shelters. The allocation of these facilities requires a detailed understanding of natural and human factors, which has led researchers to explore various multi-criteria decision-making (MCDM) techniques, GIS tools, and spatial analysis approaches. The existing literature covers a wide spectrum of methodologies used for evaluating and optimizing the site selection process, each contributing unique insights into the challenges and best practices in disaster preparedness and emergency response.

Nayyeri et al. (2024) conducted a comprehensive study titled "Location of Disaster Management Bases Using Spatial Analysis" that investigates optimal site selection for disaster management bases in Iran. Iran's susceptibility to earthquakes, particularly in regions like Nahavand City, has necessitated careful planning for relief and rescue centers. This research integrates GIS with decision-making models such as TOPSIS, VIKOR, fuzzy logic, and artificial neural networks. By evaluating 12 different indicators, Nayyeri et al. demonstrate that smaller study areas tend to yield more precise site selection results. The combination of spatial analysis tools and multi-criteria decision-making methods provides a robust framework for enhancing pre-crisis planning. This approach is particularly crucial in seismically active areas, where the need for accurate and rapid deployment of resources is high.

In response to the COVID-19 pandemic, shelter location planning gained new significance, especially for healthcare facilities designed to manage overflow during health crises. Hu et al. (2022) explore this concept through the placement of Fangcang shelter hospitals. The authors combine the Entropy Weight Method (EWM) with the TOPSIS technique to develop an evaluation framework for selecting these shelter hospitals. Their focus is on addressing healthcare capacity issues by strategically locating facilities that can isolate and treat mild COVID-19 cases, thereby relieving pressure on traditional hospitals. The use of p-median model variants helps to incorporate capacity constraints, offering a comprehensive methodology for dealing with pandemic management and healthcare resource allocation.

Another major area of focus in the literature is the selection of shelters in post-earthquake scenarios. Ommi et al. (2022) conducted a study on shelter site selection in the Zagros province of Iran, an area characterized by frequent seismic activity. Their approach combines TOPSIS and AHP to evaluate various criteria, including environmental hazards, accessibility, proximity to necessary infrastructure, ground acceleration, slope, and elevation. Notably, Ommi et al. introduce probabilistic aftershock hazard assessment (PAHA) to address the risks associated with aftershocks. The integration of satellite imagery and digital elevation models (DEMs) allows for a more informed selection of shelter locations that account for geotechnical and environmental factors. The emphasis on using multiple layers of data to assess potential shelter sites contributes significantly to the precision and resilience of disaster management strategies in seismically vulnerable areas.

The location planning of Emergency Medical Service Facilities (EMSFs) in earthquake-prone areas presents unique challenges, especially given the need for immediate medical care post-disaster. Kenan (2022) presents a comprehensive framework for selecting EMSF sites in Wenchuan, China. This study employs coupled multi-hazard assessment (CMHA) techniques alongside MCDM methods to establish an evaluation system based on terrain, safety, resources, and transportation. By integrating GIS tools for spatial analysis, Kenan (2022) effectively illustrates how EMSF location planning can be optimized through the use of interval AHP and TOPSIS. The findings underscore the particular importance of EMSF accessibility in rural areas where infrastructure may be less developed. The use of sensitivity analysis in this study highlights the robustness of the proposed framework, offering a valuable contribution to the literature on EMSF planning in areas vulnerable to natural disasters.

Fuzzy multi-criteria decision-making models have also proven instrumental in managing the uncertainty inherent in disaster management. Geng et al. (2022) propose a hybrid decision support model that combines Fuzzy AHP, Fuzzy TOPSIS, and multi-objective optimization to select emergency shelter locations. The authors emphasize that factors such as topography, slope, geology, and energy facilities must be considered to enhance both the safety and efficiency of shelter sites. The model aims to optimize key objectives, including minimizing evacuation distances, enhancing facility suitability, and reducing operational costs. The balance between qualitative assessments and quantitative operational efficiency is particularly important in high-risk environments where shelter placement needs to adapt quickly to evolving disaster conditions.

A related study by Gerasimenko et al. (2021) further explores the use of fuzzy methodologies by employing intuitionistic fuzzy sets within a modified TOPSIS framework. The research focuses on the challenges associated with shelter selection during evacuations, especially under uncertain and dynamic conditions. The use of intuitionistic fuzzy sets allows for the incorporation of expert doubts and uncertainties, thus enabling more accurate prioritization of shelter sites in disaster scenarios. This methodology provides valuable insights for improving the robustness of emergency shelter selection, particularly in cases where evacuation plans are frequently revised due to changing conditions.

Urban shelter planning is another significant area of focus, as cities often face unique challenges related to population density and infrastructure constraints. Wang (2019) provides a detailed evaluation of 28 emergency shelters in Tianjin, China, using a model that integrates AHP with TOPSIS. The index system established by Wang (2019) includes factors such as safety, accessibility, and effectiveness, with AHP used to determine the weights of these criteria. The findings indicate that many shelters suffer from uneven distribution and insufficient capacity, highlighting the importance of structured assessments to ensure that urban centers have adequate emergency resources. Wang's study emphasizes the critical need for an urban disaster management strategy that accounts for shelter quality and spatial distribution.

The hybridization of MCDM methods, particularly the combination of fuzzy AHP with TOPSIS, has been widely applied in disaster management to tackle complex decision-making problems. Trivedi et al. (2017) demonstrate the effectiveness of this approach in their study of shelter site selection in Nepal's Gorkha district, which was heavily impacted by the 2015 earthquakes. By using fuzzy AHP to assess qualitative criteria such as terrain and safety, and TOPSIS to rank the most suitable shelter sites, this hybrid approach addresses both the uncertainty and the need for a precise decision-making process in post-earthquake environments. Trivedi et al.'s study illustrates how the integration of qualitative and quantitative methods enhances the robustness of site selection in disaster-prone areas.

In addition to natural disasters, the challenges of selecting shelter sites in conflict zones have also been examined. Çetinkaya et al. (2021) employ GIS and Multi-Criteria Decision Analysis (MCDA) to assess shelter locations in Idlib, Syria. This study uses input from local residents to evaluate four alternative locations based on various criteria, highlighting how spatial and non-spatial data can be effectively combined to inform humanitarian logistics. The authors demonstrate the efficacy of GIS and MCDA in selecting shelter sites that meet both immediate needs and long-term resilience goals in complex conflict environments.

Advanced MCDM techniques continue to evolve, providing new tools for addressing data inconsistencies and uncertainties in shelter selection. Song et al. (2019) introduce a QUALIFLEX-based approach that incorporates interval rough number transformation to address the vagueness and inconsistencies commonly found in disaster data. This method proves particularly useful in the context of shelter site selection, where precise data is often unavailable. Similarly, Fei et al. (2024) employ Evidential Linguistic Term Sets (ELTS) with the ELECTRE method to address decision-making under uncertain conditions. These advanced methodologies allow for a more nuanced approach to shelter selection by integrating subjective expert evaluations, thereby improving decision-making reliability in humanitarian logistics.
Geographic Information Systems (GIS) play an essential role in evaluating the spatial suitability of emergency shelters, particularly in urban settings. Yao et al. (2021) assess public open spaces in Greater Victoria, Canada, as potential emergency shelters for earthquake evacuation. By integrating the TOPSIS method with GIS, Yao et al. create a model that can be applied to other Canadian cities for emergency preparedness planning. Their research emphasizes the importance of ensuring that the spatial distribution of shelters aligns with population density, offering a framework for cities to adapt their disaster response plans based on the unique needs of their urban populations.

The optimization of shelter locations in densely populated urban environments remains a critical issue, particularly in cities like Shanghai, which are prone to a variety of natural disasters. Wang et al. (2022) employ a multi-criteria decision-making framework that integrates AHP, TOPSIS, and fuzzy optimization to evaluate the effectiveness, safety, and fairness of shelter locations. By constructing an indicator system to assess existing shelters, the study identifies critical deficiencies in their distribution, ultimately offering recommendations to urban planners for improving disaster response infrastructure. This research adds to the literature by emphasizing the need for careful urban planning to optimize shelter accessibility and ensure that shelters meet the diverse needs of urban populations.

Saeidian et al. (2018) take a hybrid approach to emergency shelter allocation in Tehran, combining TOPSIS with GIS tools and meta-heuristic algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). This study finds that PSO provides higher accuracy and convergence speed compared to ACO, demonstrating the effectiveness of hybrid models in optimizing emergency shelter allocation in high-risk urban areas. By incorporating factors such as proximity to fault lines, population density, and land use, the study provides a comprehensive approach that highlights the value of combining different optimization techniques to address the complex challenges of disaster management.

Further extending the literature, Geng et al. (2020) emphasize the importance of categorizing shelters based on their purpose—whether for basic living needs or psychological and medical services. The authors propose a model that incorporates both qualitative and quantitative considerations, such as topography, geological conditions, and the storage of essential materials. By using fuzzy AHP and TOPSIS, this model provides a more nuanced evaluation of shelter alternatives, offering insights for policymakers aiming to enhance both disaster response efficiency and humanitarian logistics.

Advanced MCDM techniques are also applied to address the challenges of complex, uncertain decision-making scenarios. Akram et al. (2023) introduce two practical multi-criteria decision-making approaches—PROMETHEE I and PROMETHEE II—using spherical fuzzy sets for evaluating the construction sites of Fangcang shelter hospitals during the COVID-19 pandemic. By integrating the Shannon entropy method for determining criteria weights and comparing alternatives based on key factors such as traffic convenience and environmental protection, Akram et al. demonstrate the effectiveness of these advanced methods in handling uncertain conditions. The comparison with spherical fuzzy TOPSIS highlights the robustness of these approaches in supporting disaster response planning during health emergencies.

In conclusion, the literature highlights the importance of adopting a diverse range of methodologies to improve the site selection of disaster management facilities. Whether through GIS-based spatial analyses, fuzzy logic, or advanced MCDM frameworks, these studies provide valuable insights into balancing qualitative and quantitative criteria for effective shelter planning. Collectively, the research underscores the importance of strategic infrastructure planning in enhancing disaster preparedness and response capabilities, ensuring public safety, and optimizing the use of resources in vulnerable regions.

Table 2-1: Literature Review

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
1	2024	Location of Disaster Management Bases Using Spatial Analysis	Develop a model for the optimal placement of relief and rescue centers in Iran, using various spatial analysis and MCDM methods to minimize vulnerability and improve disaster preparedness and response effectiveness.	GIS, VIKOR, Fuzzy Logic, Artificial Neural Networks, Euclidean Distance Method, ARCGIS and IDRISI	TOPSIS	Natural Criteria: Distance from fault lines, Flood zones, Waterway networks, Slope of the area, Geomorphology, Landslide areas, Geological status. Human Criteria: Distance from communication lines (roads), Distance from urban population centers, Distance from rural centers, Population density, Land use.	Potential locations for relief and rescue centers
2	2024	An evidential linguistic ELECTRE method for selection of emergency shelter sites	The subject of the paper is emergency shelter site selection.	Evidential Linguistic Term Set (ELTS) Belief Function Theory (BFT) Uncertainty Measure, Dissimilarity Measure, Expectation Function	ELECTRE	Safety, Accessibility, Equilibrium, Effectiveness, Environment	Emergency shelter sites
3	2024	A location-allocation optimization model for post-earthquake emergency shelters using network-based multi-criteria decision-making	The paper discusses selecting and allocating emergency shelters (ESs) after an earthquake by using multi-criteria decision-making methods (MCDM) and network-based analysis.	CRITIC MWCCR GIS Multi-objective models	TOPSIS	Proximity to faults Proximity to fire stations Proximity to hospitals Proximity to main roads Area of the emergency shelters (ESs) Population vulnerability (based on age, gender, and marital status)	Emergency Shelters
4	2023	Lexicographic maximum dynamic evacuation modeling with partial lane reversal based on hesitant fuzzy TOPSIS	This paper addresses the problem of prioritizing shelters for evacuation during emergencies under uncertain and fuzzy conditions.	MAGDM (Multiple Attribute Group Decision Making) Triangular Fuzzy Numbers (TrFNs) Lexicographic Maximum Flow Model with fuzzy arc capacities and traversal times Sensitivity Analysis	Hesitant Fuzzy TOPSIS	Level of accessibility Capacity Reliability (security) Total expenses Extensibility	Terminals or shelters for evacuation
5	2023	Evaluation of Emergency Shelter Service Functions and Optimisation Suggestions—Case Study in the Songyuan City Central Area	The study focuses on the evaluation and optimization of the service functions of emergency shelters in Songyuan, China.	Entropy Grey correlation method Bivariate Moran Index	TOPSIS	Effectivenes, Accessibility, Safety, Rescue Responsiveness	54 emergency shelters in the central city of Songyuan

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
6	2023	A PROMETHEE based outranking approach for the construction of Fangcang shelter hospital using spherical fuzzy sets	The study aims to identify the most suitable site for establishing Fangcang shelter hospitals (FSHs) in Wuhan during the COVID-19 outbreak.	Shannon's Entropy SWAM (Spherical Weighted Arithmetic Mean)	PROMETHEE I Method PROMETHEE II Method	Traffic convenience Environmental protection Geographical position Infrastructure Regional communication convenience Capacity Reconstruction difficulty Reconstruction cost	-
7	2022	Study on the Localization of Fangcang Shelter Hospitals During Pandemic Outbreaks	Develop an evaluation framework using EWM-TOPSIS to select the best locations for Fangcang shelter hospitals and optimize the triage and referral process to minimize the spread of infectious diseases and alleviate the burden on healthcare systems.	Entropy Weight Method (EWM), Two-stage localization method, P-median model	TOPSIS	Risk of pandemic spread. Locations far from densely populated areas. Number of expected patients. Capacity to accommodate patients. Proximity to designated hospitals. Travel time between resident nodes and shelter hospitals. Proportion of patients who deteriorate from mild-to-moderate to severe conditions.	Candidate Fangcang shelter hospital locations in Xuzhou, Jiangsu Province, China. Designated higher-level hospitals for severely ill patients. Resident demand nodes (which represent discrete variable population distribution nodes or streets).
8	2022	Selection of shelters after earthquake using probabilisti	Determine appropriate temporary or fixed shelter locations by ranking vacant areas using both seismic hazard analysis and environmental factors such as distance from roads, slope, elevation, and the extent of structural damage.	Probabilistic Aftershock Hazard Analysis (PSAHA), Remote Sensing and GIS, Seismic Parameters and Ground Motion Prediction	TOPSIS, AHP	Horizontal Peak Ground Acceleration (PGA), Slope, Area of Vacant Regions, Damage Level of Vacant Regions, Distance from Roads, Elevation	Vacant regions in the area affected by the earthquake, specifically identified from pre-event Sentinel-2 satellite imagery.
9	2022	GIS-based MCDM framework combined with coupled multi-hazard assessment for site selection of post-earthquake emergency medical service facilities in Wenchuan, China	Post-earthquake emergency medical service facility (EMSF) site selection in Wenchuan, China, incorporating multi-hazard risks and accessibility.	Coupled Multi-Hazard Assessment (CMHA), GIS	TOPSIS, Interval AHP	Main Criteria: Favorability of Terrain, Safety, Resources, Transportation Sub-Criteria: Lithology, Elevation, Slope, Aftershocks, Landslides, Floods, Fires, Building, collapse, Electricity, Clean water, Medical resources, Distance to main roads, Distance to transportation hubs, Distance to potential landing pads	EMSF locations in Wenchuan, China

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
10	2022	A Hybrid Decision Support Model for Deploying Humanitarian Operations to Respond to Earthquakes	Humanitarian operations in disaster management, specifically focusing on the location and allocation of emergency facilities.	Multi-objective programming	Fuzzy TOPSIS, Fuzzy AHP	Topography, Geology, Slope, Vegetation, Power facilities, Evacuation distance, Total cost of humanitarian operations, Suitability based on qualitative factors	Candidate emergency facilities (locations for emergency living shelters and medical shelters)
11	2022	A Multi-Indicator Evaluation Method for Spatial Distribution of Urban Emergency Shelters	The paper evaluates the spatial distribution of urban emergency shelters in Shanghai, aiming to identify deficiencies in the current distribution and to improve urban emergency shelters and evacuation capacity	CRITIC Method (Criteria Importance Through Intercriteria Correlation) Fuzzy Optimization Theory Grey Correlation Analysis Real Coded Accelerated Genetic Algorithm—Projection Pursuit (RAGA-PP) Two-step Floating Catchment Area (2SFCA) Inverted Two-step Floating Catchment Area (i2SFCA)	TOPSIS AHP	Effectiveness: Effective service range, Effective number of people served, Service overlap area ratio Accessibility: Distance to nearest hospitals, fire stations, command agencies, and residential areas, Comprehensive accessibility value for residents Safety: Proximity to flammable and explosive storage areas, Slope of the shelter Suitability: Open space ratio, Potential crowdedness of emergency shelters Fairness: Service area ratio, Service population ratio, Service overlap rate, Service population gap	91 urban emergency shelters in Shanghai
12	2021	A Hybrid Approach of VIKOR and Bi-Objective Decision Model for Emergency Shelter Location–Allocation to Respond to Earthquakes	The paper addresses the problem of emergency shelter location-allocation during an earthquake in disaster management.	Entropy method for objective weighting of criteria, Bi-objective programming, ε-constraint method	Fuzzy-VIKOR	Topography, Geological type, Slope, Vegetation, Power facilities	Candidate locations for emergency shelters
13	2021	Minimum cost lexicographic evacuation flow finding in intuitionistic fuzzy networks	The paper focuses on evacuation planning in emergencies, specifically modeling minimum cost evacuation flows in intuitionistic fuzzy networks where the uncertainty of parameters is high.	Lexicographic flow modeling, Non-standard subtraction operation	TOPSIS	Capacity, transportation cost (time), and the priority of the sinks (which may depend on urgency of evacuation and availability)	Potential shelters or safe areas for evacuees

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
14	2021	Decision Support System for Temporary Shelter Selection Using Hybrid AHP and TOPSIS	This paper explores the use of AHP and TOPSIS methodologies for selecting the most suitable emergency shelters.	Hamming and Euclidean distance measures	TOPSIS, AHP	Influential factors relevant to emergency shelter selection, such as location, capacity, risk level, etc.	Several emergency shelters
15	2021	Emergency Shelter Site Selection in Maar ShurinCommunity of Idlib (Syria)	Shelter site selection in the conflict zone of Idlib, Syria.	GIS	TOPSIS	Area (larger is better) Electricity access (larger is better) Proximity to water resources (lower is better) Land cost (lower is better) Accessibility via paved roads (excluded in this specific case due to uniform values across alternatives)	Four alternative sites located in the north, south, west, and east parts of Idlib, Syria.
16	2021	A GIS-Based System for Spatial-Temporal Availability Evaluation of the Open Spaces Used as Emergency Shelters: The Case of Victoria, British Columbia, Canada	The paper focuses on evaluating public open spaces in Greater Victoria, British Columbia, as emergency shelters for post-earthquake evacuation using a multi-criteria decision-making approach.	GIS Entropy Coupling Analysis	TOPSIS	Safety: Building collapse risk, Fire hazard (proximity to gas stations) Accessibility: Road accessibility, Rescue response speed (distance to nearest fire station and hospital) Capability: Shelter capacity (area divided by 2 square meters per person)	Public open spaces in Greater Victoria, Canada
17	2020	A Hybrid Decision Support Model for Deploying Humanitarian Operations to Respond to Earthquakes	Humanitarian operations in disaster management, focusing on the selection and optimization of emergency facility locations during natural disasters.	Multi-objective optimization	Fuzzy TOPSIS, Fuzzy AHP	Qualitative Criteria: Topography, Geology, Slope, Vegetation, Power facilities. Quantitative Criteria: Evacuation distance, Cost of humanitarian operations, Suitability of facilities.	Candidate emergency facilities: Shelters providing essential living services, Shelters providing both essential services and medical aid/psychological attention
18	2020	Site Selection of the Colombian Antarctic Research Station Based on Fuzzy-Topsis Algorithm	The paper focuses on the optimal site selection for a temporary Colombian scientific research base in Antarctica, which aims to minimize operational costs while adhering to geographic, logistical, and geopolitical constraints.	GIS Fuzzy set	TOPSIS	Proximity to other scientific stations, Water supply (from glaciers), Proximity to an airstrip, A sheltered bay, Existence of ship anchoring areas, Meteorological conditions, Geopolitical restrictions (Madrid Protocol), Antarctic Specially Protected Areas (ASPA)	Ten alternate locations in Antarctica

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
19	2020	Multi-Criteria Location Model of Emergency Shelters in Humanitarian Logistics	The paper focuses on the optimization of emergency shelter site selection considering various qualitative and quantitative factors impacting the needs of disaster victims.	Multi-objective Optimization Extension of Fuzzy Numbers	TOPSIS AHP	Topography Geological type Slope Vegetation Power facilities Sanitation system	Type I Shelters: Provide only basic living services. Type II Shelters: Provide both life and medical assistance services.
20	2019	Research on the Suitability of the Emergency Shelter in Tianjin	Evaluating the suitability of emergency shelters in Tianjin, China, using the TOPSIS methodology for multi-criteria decision-making.	Expert Scoring & Questionnaire	TOPSIS, AHP	Effectiveness: Emergency evacuation function facility, Capacity, Per capita shelter area Safety: Distance to major hazard sources, Avoid geological and hydrological hidden dangers Accessibility: Distance from recent medical institutions, Distance from the recent public security organs, Distance to the nearest fire base, Evacuated road grade	28 emergency shelters in Tianjin, including sites like Central Park, Weinan Park, Galaxy Square, People's Park, Hexi Park, Yuhe Park, Changhong Park, etc.
21	2019	Shelter planning for uncertain seismic hazards using multicriteria decision approach: A case of Nepal earthquake	The paper addresses the location and relocation problem for temporary shelters under uncertain seismic damage scenarios, specifically in the context of the 2015 Nepal earthquake.	Weighted Goal Programming (WGP)	TOPSIS, AHP	Favourability of terrain, Hygiene and sanitation system,Safety and security Proximity (including distance from market/warehouses, main roads, healthcare, transportation hubs), Soil hardness, Topography, Slope, Presence of trees, Drinking water availability, Drainage and sewage infrastructure, Solid waste disposal, Electrical infrastructure (electricity, telecommunication), Community infrastructure (educational, recreational facilities), Transportation capacity (air traffic, road conditions), Type of ownership (private or public land)	13 candidate sites in the Gorkha district of Nepal

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
22	2019	Sustainable shelter-site selection under uncertainty: A rough QUALIFLEX method	The study focuses on the shelter site selection problem in the context of humanitarian logistics, specifically during the pre-disaster phase of emergency logistics.	Interval Rough Number Transformation Comparative Analysis	QUALIFLEX	Logistic efficiency Policy friendliness Environmental conservation Social sustainability Weight factors based on group decision-making	Potential shelter sites in Wenchuan County
23	2018	Optimized Location-Allocation of Earthquake Relief Centers Using PSO and ACO, Complemented by GIS, Clustering, and TOPSIS	The paper focuses on the selection and allocation of temporary relief centers in response to earthquakes in Tehran, specifically in District 1.	GIS Clustering Method Particle Swarm Optimization (PSO)	TOPSIS	Present land use of the relief centers Area of the relief centers Distance of the relief centers from fault lines Population around the relief centers Slope of the relief center location Distance of the relief centers from the main routes Distance of the relief centers from each other Distance of parcels from the relief centers	Relief center sites in District 1 of Tehran
24	2017	Urban Emergency Shelter Site Selection	The paper focuses on improving the site selection process for emergency shelters during disasters.	Entropy Method, Gray Correlation Analysis Method, Social Choice Methods	TOPSIS, AHP	Security: Distance between the emergency shelter and the gas station. Accessibility: Distance between the hospital and the fire station. Reliability: Effective space ratio of the shelter (simplified to the area occupied by the shelter).	36 candidate sites for emergency shelters

#	Year	Title	Subject	Other Methodologies	MCDM	Criteria	Alternatives
25	2017	Prioritizing emergency shelter areas using hybrid multi-criteria decision approach: A case study	The paper focuses on the problem of selecting emergency shelter sites in the context of disaster management.	Fuzzy logic	TOPSIS, AHP	Favourability of terrain: Soil hardness, Topography, Slope, Presence of trees Electrical infrastructure: Electricity, Telecommunication facility Hygiene and sanitation system: Drinking water, Drainage system and sewage infrastructure, Solid waste disposal Community infrastructure: Educational facilities, Recreational facilities Safety and security: Safety from landslides, flooding, etc. Fire safety: Warning systems, Transportation capacity, Air traffic handling Condition of local road infrastructure: Distance from market/warehouses, Distance from main roads, Distance from healthcare facilities, Distance from transportation hubs, Distance from disaster debris storage sites	Candidate locations for shelter sites
26	2014	Urban emergency shelter locations for earthquake disaster using time-satisfaction-based maximal covering location model	The paper addresses the problem of selecting optimal urban emergency shelter locations for earthquake disaster preparedness.	Maximal Covering Location Model Genetic Algorithm and Particle Swarm Optimization (PSO)	TOPSIS	Time satisfaction function for supported units Shelter locations' distance from evacuees Maximal coverage of evacuee distribution Satisfaction level of support departments Evacuee distribution and coverage	Urban emergency shelter locations
27	2013	Study on site selection of resident emergency congregate shelters based on combination weighting TOPSIS	The paper focuses on evaluating and selecting resident emergency congregate shelters in cities and towns.	Entropy	TOPSIS, AHP	3 first-level indices: Risk of hazard, Location & size, Emergency function-ensuring infrastructure 9 second-level indices (which are sub-criteria under the first-level ones, though they are not listed specifically here).	Candidate emergency shelters (though the specific alternatives aren't listed, they refer to different potential shelter sites)

Chapter 3

Methodology

This chapter presents the methodological framework developed for ranking emergency shelters in the event of natural disasters. The primary method used in this study is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), which is integrated with entropy-based weighting methods to address the limitations associated with criterion weight determination in TOPSIS. Specifically, this research combines Shannon (1948) entropy and Wen et al. (1998) entropy to calculate objective weights, thereby improving the accuracy and robustness of the shelter ranking process.

3.1 Objective Criteria Weighting in MCDM

In MCDM, determining the relative importance or weight of each criterion is essential to achieving a balanced evaluation of alternatives. Weighting methods generally fall into two categories: subjective weights, based on expert judgment, and objective weights, derived directly from the decision matrix. This research focuses on the latter, using entropy-based techniques to calculate weights objectively. Entropy methods are particularly useful in reducing bias by identifying patterns within data and assessing the significance of each criterion.

3.1.1 Shannon Entropy-Based Weight Calculation

The concept of entropy, introduced by Shannon (1948), provides a means to evaluate the degree of variability in data, which reflects the informativeness of each criterion. The entropy weight calculation process for a criterion in the decision matrix involves the following steps:

1. **Construct the Decision Matrix**: Let D represent the decision matrix, where D consists of m alternatives and n criteria.

$$\mathrm{D} = \left[x_{ij}\right]_{m\times n} = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{pmatrix} C_1 & C_2 & .. & C_n \\ x_{11} & x_{12} & .. & x_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & .. & x_{mn} \end{pmatrix} \tag{3.1}$$

2. **Normalize the Decision Matrix**: Normalize the values in matrix D, where each entry x_{ij} is converted to a relative scale to form matrix R, given by:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \qquad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \qquad (3.2)$$

3. **Calculate Entropy**: For each criterion j, calculate entropy E_j using:

$$E_j = -\frac{1}{ln\, m} \sum_{i=1}^{m} r_{ij}\, ln\, r_{ij}, \qquad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \qquad (3.3)$$

$\frac{1}{ln\, m}$ is a constant to ensure $0 \leq E_j \leq 1$.

4. **Determine the Degree of Diversification**: The degree of diversification d_j for criterion j is obtained by:

$$d_j = 1 - E_j, \qquad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \qquad (3.4)$$

5. **Calculate Weights**: The weight w_j of each criterion j is determined by normalizing d_j:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} = \frac{1-E_j}{n - \sum_{j=1}^{n} E_j}, \qquad (3.5)$$

where $i = 1,2,...,m$ and $j = 1,2,...,n$.

Thus:

$$w_j = \frac{1 + \frac{1}{ln\, m} \sum_{i=1}^{m} r_{ij}\, ln\, r_{ij}}{\sum_{j=1}^{n}(1 + \frac{1}{ln\, m} \sum_{i=1}^{m} r_{ij}\, ln\, r_{ij})} = \frac{1 + \frac{1}{ln\, m} \sum_{i=1}^{m} r_{ij}\, ln\, r_{ij}}{n + \sum_{j=1}^{n}(\frac{1}{ln\, m} \sum_{i=1}^{m} r_{ij}\, ln\, r_{ij})} \qquad (3.6)$$

This weighting process enhances the robustness of the model by ensuring that criteria with greater variability, and therefore more discriminative power, have a higher influence on the overall ranking.

3.1.2 Wen Entropy-Based Weight Calculation

Wen et al. (1998) developed an entropy-based method that introduces a mapping function to reflect the relative significance of criteria. The function is designed to satisfy key properties, such as symmetry around 0.5 and monotonicity, and it reaches its maximum at x = 0.5. The steps for calculating criterion weights using Wen entropy are as follows:

1. **Normalization of the Original Matrix**: Normalize the original decision matrix D by ensuring that each criterion aligns with maximization (beneficial criteria) or minimization (non-beneficial criteria). This is based on two references Li et al. (2011), and Ipyk and Adaly (2017).

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - Min\, x_{ij}}{Max\ x_{ij} - Min\, x_{ij}}, & \text{if j is a benefit criterion} \\[2ex] \dfrac{Max\, x_{ij} - x_{ij}}{Max\ x_{ij} - Min\, x_{ij}}, & \text{if j is a cost criterion} \end{cases} \tag{3.7}$$

2. **Calculate Indicator Sums**: For each indicator, calculate the total sum across all alternatives.

$$D_j = \sum_{i=1}^{m} r_{ij}\,, \qquad \text{where } i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n. \tag{3.8}$$

3. **Apply Mapping Function**: Use the mapping function $W_e(x)$ to calculate the entropy values e_j for each criterion. This function captures both the variability and significance of the data in each criterion.

$$W_e(x) = x\, e^{(1-x)} + (1-x)e^{x} - 1 \tag{3.9}$$

$$e_j = \frac{1}{0.64782m} \sum_{i=1}^{m} w_e\left(\frac{r_{ij}}{D_j}\right) \tag{3.10}$$

where i = 1,2,...,m and j = 1,2,...,n.

$$e_j = \frac{1}{0.64782m} \sum_{i=1}^{m} \left(\frac{r_{ij}}{D_j}\, e^{\left(1 - \frac{r_{ij}}{D_j}\right)} + \left(1 - \frac{r_{ij}}{D_j}\right) e^{\frac{r_{ij}}{D_j}} - 1 \right) \tag{3.11}$$

where i = 1,2,...,m and j = 1,2,...,n.

4. **Calculate Weights**: Finally, determine the weights by normalizing the entropy values, ensuring each weight reflects the relative importance of its criterion.

$$E = \sum_{j=1}^{n} e_j \,, \qquad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \tag{3.12}$$

$$W_j = \frac{\frac{1}{n-E}\left[1 - e_j\right]}{\sum_{j=1}^{n} \frac{1}{n-E}\left[1 - e_j\right]} \,, \qquad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \tag{3.13}$$

The Wen entropy approach complements Shannon entropy by adjusting for the importance level among criteria, resulting in a balanced yet nuanced weighting system for the decision matrix.

3.2 Mixed Objective Weighting Model (ϕ, λ Feasibility)

To create a more robust model that leverages both Shannon and Wen entropy, this study proposes a mixed weighting approach. This method combines the two objective weights in proportions defined by mixing parameters ϕ and λ, satisfying $\phi + \lambda \leq 1$ and $\phi, \lambda \geq 0$. The combined weight W_j for each criterion is given by:

$$w_j = \phi \, w_j^{Shanon} + \lambda \, w_j^{Wen}, \qquad \text{where } j = 1,2,...,n. \tag{3.14}$$

Then $w_j(\phi, \lambda)$ can be written as:

$$w_j(\phi, \lambda) = \frac{\phi}{\phi + \lambda} \left(\frac{1 + \frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}}{n + \sum_{j=1}^{n} (\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij})} \right) + \frac{\lambda}{\lambda + \phi} \left(\frac{\frac{1}{n - E}[1 - e_j]}{\sum_{j=1}^{n} \frac{1}{n - E}[1 - e_j]} \right) \tag{3.15}$$

If $\phi = 0$ then $w_j(\phi, \lambda)$ will be $w_j(\lambda)$:

$$w_j(\lambda) = \left(\frac{\frac{1}{n - E}[1 - e_j]}{\sum_{j=1}^{n} \frac{1}{n - E}[1 - e_j]} \right) \tag{3.16}$$

If $\lambda = 0$ then $w_j(\phi, \lambda)$ will be $w_j(\phi)$:

$$w_j(\phi) = \left(\frac{1 + \frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}}{n + \sum_{j=1}^{n} (\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij})} \right) \tag{3.17}$$

The mixing method can be generalized as bellow:

$$w_j(\phi, \lambda) = f_1(\phi, \lambda) \left(\frac{1 + \frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}}{n + \sum_{j=1}^{n} (\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij})} \right) + f_2(\phi, \lambda) \left(\frac{\frac{1}{n - E}[1 - e_j]}{\sum_{j=1}^{n} \frac{1}{n - E}[1 - e_j]} \right) \tag{3.18}$$

Where $0 \leq f_1(\phi, \lambda) \leq 1$, and $0 \leq f_2(\phi, \lambda) \leq 1$ are all nonnegative and $\sum_{k=1}^{2} f_k(\phi, \lambda) = 1$.

This mixed approach provides flexibility, allowing for a customized balance between the two entropy-based weights. The combined model captures the strengths of both methods: the data-driven accuracy of Shannon entropy and the importance-adjusted weighting of Wen entropy, reducing the risk of bias in weight determination.

This innovative approach to calculate weights has never been used in the emergency shelter selection context.

3.3 TOPSIS Methodology

The TOPSIS model formulation, as presented by Hwang et al. (1995), Triantaphyllou (2000), and Malczewski (1999, 2006), is expressed in a matrix format where columns represent attributes or criteria, and rows list the alternatives. According to Triantaphyllou (2000), the TOPSIS method assumes that criteria exhibit a monotonic utility (either increasing or decreasing), facilitating the definition of ideal solutions. For a Multi-Criteria Decision-Making (MCDM) problem with m alternatives ($A_1,\ldots,A_m$) and n decision criteria ($C_1,\ldots,C_n$):

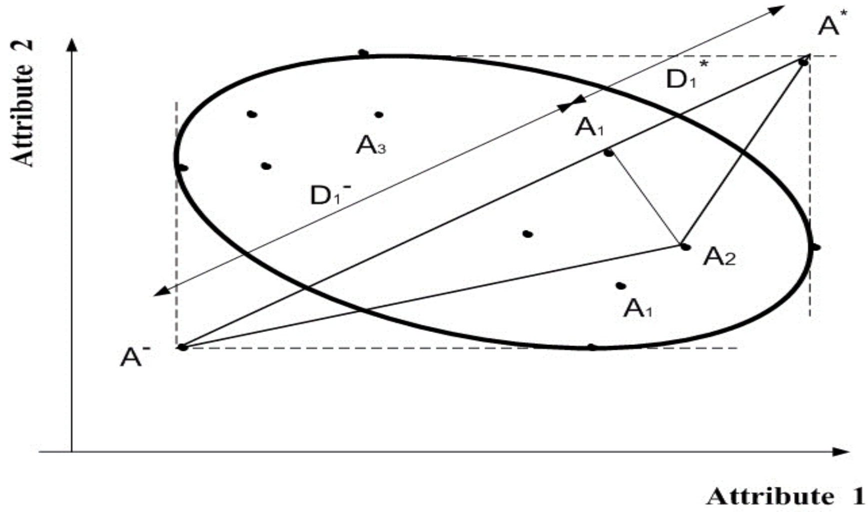

Figure 2: Euclidean Distances to Positive-Ideal and negative-Ideal Solutions in Two-Dimensional Space. SOURCE: Hwang and Yoon (1981).

Each alternative is evaluated with respect to the n criteria. The ratings assigned to the alternatives for each criterion form a decision matrix denoted as $X = (x_{ij})_{m\times n}$. Let $w = (w_1,\ldots,w_n)$ represent the relative weight vector for the criteria, satisfying the condition $\sum_{i=1}^{n} w_i = 1$. TOPSIS in this study is applied to rank shelters based on their proximity to ideal and anti-ideal solutions. This section outlines the steps used in the TOPSIS model:

1. **Normalize the Decision Matrix**: Convert the decision matrix into a normalized form, where each value r_{ij} reflects the relative performance of alternative i under criterion j.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad \text{where } i = 1,2,...,m \text{ and } j = 1,2,...,n. \quad (3.19)$$

2. **Weighted Normalized Decision Matrix**: Apply the criterion weights obtained from the mixed model to the normalized decision matrix, forming matrix V:

$$v_{\text{ij}} = w_j \,.\, r_{ij} \,, \tag{3.20}$$

where i = 1,2,...,m and j = 1,2,...,n.

$$V = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_1 r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_2 r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \tag{3.21}$$

3. **Identify Ideal and Anti-Ideal Solutions**: Define the positive ideal solution A^+ and the negative ideal solution A^-:

$$A^+ = (Max\ v_{ij} \mid j \ \epsilon\ benefit\ criteria, Min\ v_{ij} \mid j\ \epsilon\ cost\ criteria) \tag{3.22}$$

$$A^- = (Min\ v_{ij} \mid j \ \epsilon\ benefit\ criteria, Max\ v_{ij} \mid j\ \epsilon\ cost\ criteria) \tag{3.23}$$

4. **Calculate Separation Measures**: Determine the Euclidean distances of each alternative from the ideal and anti-ideal solutions:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^+\right)^2} \tag{3.24}$$

where i = 1,2,...,m and j = 1,2,...,n.

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2} \tag{3.25}$$

where i = 1,2,...,m and j = 1,2,...,n.

5. **Relative Closeness to the Ideal Solution**: Compute the relative closeness RC_i of each alternative to the ideal solution, where a higher RC_i indicates a preferable alternative:

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-}\,, \qquad \text{where } i = 1,2,\ldots,m. \tag{3.26}$$

6. **Ranking Alternatives**: Rank the alternatives based on RC_i, with the shelter closest to 1 in RC_i considered the most suitable.

3.4 Criteria definitions

Table 3-1: Criteria Definition

#	Title	Definition
1	Pet-friendly	Indicates whether the hotel allows guests to stay with pets.
2	On-Site Restaurant	Whether the hotel has a restaurant located within the premises.
3	Proximity to Airport	Measures how close the hotel is to city international airport.
4	Nearby Amenities	Assesses if the hotel is surrounded by stores, restaurants, and entertainment.
5	Room Amenities (Microwave)	Whether a microwave is available in standard rooms.
6	Rooms with 2 Beds	If the hotel offers rooms with two separate beds.
7	Security Measures	Whether the hotel has safety protocols like surveillance, staff presence, secure access.
8	Walking Space for Pets	Assesses if there's an area for walking pets outside the hotel.
9	Accessibility	Whether the hotel accommodates guests with disabilities.
10	De-stressing Spaces	If the hotel provides areas like a spa, sauna, or relaxation lounge.
11	Support for Different Age Groups	Whether the hotel has facilities for both children and seniors.
12	Space for Nurse	If the hotel has a private area or room suitable for medical personnel.
13	Facilities for Detaining Individuals	Whether the hotel can temporarily isolate or secure high-risk individuals.
14	Emergency Power Supply	Whether the hotel has backup generators or emergency power systems.
15	Capacity (Rooms)	The total number of rooms in the hotel.
16	Proximity to Hospitals	Distance from the hotel to the nearest medical facility.
17	Parking Space Availability	Whether the hotel has sufficient parking for arriving numerous guests at the same time and emergency use.
18	Structural Safety and Resilience	Assesses building strength and hazard resistance.

19	Distance to Hazard-Prone Areas	Measures proximity to areas at risk of flooding or other hazards.
20	Food Storage and Cooking Facilities	Whether guests have access to food prep/storage (fridge, kitchenette).
21	Accessibility to Public Transportation	Proximity to bus stops or transit stations.
22	Distance from Main Roads	How close the hotel is to major city routes or highways.
23	Availability of Multi-Purpose Rooms	Whether the hotel offers flexible space for meetings, medical use, or group activities.
24	Availability of Laundry Facilities	Whether laundry machines or services are provided.

The criteria used in this study were identified through a combination of three sources: a review of recent academic and practical research, insights gathered from interviews with emergency management officials, and internal brainstorming sessions. These criteria reflect both the established knowledge in the field and the specific needs voiced by professionals responsible for managing real-world emergency responses.

In this study, the evaluation of emergency shelter alternatives relies on a carefully structured set of 24 criteria, categorized as either benefit or cost based on their contribution to shelter suitability and safety during natural disasters. This classification is critical, as it directly influences how each criterion is normalized and incorporated into the TOPSIS framework.
Benefit criteria are those for which higher values (or affirmative responses, such as "Yes") are considered more favorable. These criteria represent positive features that enhance the quality, accessibility, or resilience of a shelter, making it more suitable to host evacuees under emergency conditions. For instance, criteria such as *Pet-Friendly* and *Walking Space for Pets* were considered benefits because allowing pets and providing space for their movement can increase evacuee willingness to relocate to the shelter and reduce stress, especially for families with animals. Similarly, *On-Site Restaurant*, *Nearby Amenities*, *Microwaves in Rooms*, and *Availability of Food Storage and Cooking Facilities* contribute to the comfort and autonomy of evacuees and were thus treated as benefit criteria.

Additional benefit factors include *Rooms with Two Beds*, *De-stressing Spaces*, and *Support for Different Age Groups*, which all support the physical and mental well-being of diverse evacuee populations. *Accessibility* ensures inclusivity for individuals with disabilities, while *Security Measures*, *Emergency Power Supply*, and *Structural Safety and Resilience* are vital to ensuring continuous operation and safety during and after the disaster. The presence of *Space for a Nurse* and *Facilities for Detaining Individuals* improves the shelter's capacity to manage health-related issues and behavioral risks.

Capacity (number of rooms), *Parking Availability*, *Availability of Multi-Purpose Rooms*, and *Laundry Facilities* were all categorized as benefits as they support the shelter's ability to accommodate a large number of evacuees for longer durations. Furthermore, *Accessibility to Public Transportation* was considered a benefit, as greater access to transit services allows easier evacuation logistics and post-disaster mobility.

Importantly, *Proximity to Airport* was also treated as a benefit criterion in this model. Although distance-based in nature, it was measured categorically using Yes/No, where "Yes" indicated that the shelter was close to the airport, a feature deemed beneficial in terms of accessibility for emergency logistics or for receiving external aid. Therefore, despite being proximity-related, the encoding and decision logic defined this criterion as a benefit.

On the other hand, cost criteria are those for which lower values are more desirable, representing obstacles, risks, or operational inefficiencies. For example, *Proximity to Hospitals*, *Distance from Main Roads*, and *Distance to Hazard-Prone Areas* were initially expected to fall into this category, as they all relate to accessibility or exposure to risk. However, upon closer inspection, *Distance to Hazard-Prone Areas* was recategorized as a benefit criterion, because higher values, i.e., greater distance from flood zones or forest fires, translate to increased safety and resilience. Thus, in this context, more distance is better, not worse.

Proximity to Hospitals and *Distance from Main Roads*, however, remained cost criteria. In both cases, shorter distances are beneficial: a hospital nearby ensures faster medical response, and closeness to major roads improves logistical access for both incoming aid and outgoing evacuees. These two were measured numerically (in kilometers), and thus, a lower value indicates higher performance, aligning them with the cost criterion category.

As a result, the final classification reflects both the practical intent behind each criterion and how it was operationalized in the dataset. For binary (Yes/No) variables, "Yes" typically indicated a presence of a desirable feature and was treated as a benefit. For numerical variables, such as distances or capacities, the classification depended on whether higher or lower values improved the shelter's utility. This careful distinction ensures that the model properly accounts for the real-world implications of each criterion in an emergency context and allows for accurate entropy-based weighting and TOPSIS ranking.

The primary goal of selecting these criteria is to ensure that individuals displaced by natural disasters can remain in the designated shelters until their homes become livable again. This approach is crucial because relocating evacuees multiple times not only causes additional stress for affected individuals but also places a significant burden on emergency response resources. Each relocation requires time, logistical coordination, and financial support, making it essential to choose shelters that are capable of supporting medium- to long-term stays. Therefore, the selected criteria help identify shelters that minimize the need for further relocation, ensuring both human well-being and operational efficiency. Criteria will be mentioned as C_1 to C_{24} according to the provided list in the next section.

3.5 Data driven Approach

The proposed framework for emergency shelter ranking is inherently data-driven, meaning that the weighting and prioritization of criteria are determined from observed, measurable data rather than from subjective judgments alone. In a data-driven system, model parameters are inferred directly from the characteristics of the dataset, allowing the decision-making process to adapt to the specific context of the problem and reduce bias. This approach ensures that the results are grounded in the actual distributions, relationships, and variability of the available data, enhancing objectivity, reproducibility, and robustness.

In traditional MCDM methods, the assignment of criteria weights often relies on expert opinions, such as through the Analytic Hierarchy Process (AHP) or fuzzy AHP. While expert input is valuable, it can introduce personal biases and inconsistencies. In contrast, the present study applies objective weighting methods, specifically Shannon entropy and Wen entropy, which quantify the significance of criteria based solely on the dataset's statistical properties.

Shannon entropy, derived from information theory, measures the degree of disorder or uncertainty in a dataset. In the context of criteria weighting, it quantifies the variability of each criterion across all alternatives. A criterion with high variability (large differences between alternatives) provides more discriminative power and therefore receives a higher weight. Conversely, a criterion with low variability offers less differentiation and thus receives a lower weight. While Shannon entropy focuses on the distributional variability of criteria, Wen entropy emphasizes the magnitude and proportional importance of criteria values. It captures the dispersion of normalized criterion scores in a different mathematical form, ensuring that criteria with more influential magnitude patterns receive appropriate emphasis. Wen entropy is particularly effective when dealing with datasets where some criteria have dominant ranges or when differences in scale could distort the perceived importance.

By using Wen entropy, the model incorporates a second, independent lens for assessing the importance of each criterion, complementing the insights obtained from Shannon entropy. This dual-entropy approach ensures that both distributional spread and value magnitude are considered in the weighting process. The integration of Shannon and Wen entropy allows the model to leverage two complementary measures of data informativeness. While each method individually captures a distinct aspect of variability, their combination yields a more holistic and stable set of weights. Relying on a single entropy measure could overlook certain nuances in the data; therefore, combining both strengthens the robustness of the weighting system.

The selection of φ can itself be data-driven by evaluating the stability and performance of the model across different parameter values, ensuring that the chosen balance maximizes discriminative ability and consistency in rankings. This tunable integration makes φ a data-adaptive mechanism, allowing the model to respond to the nature of the dataset rather than applying a fixed, arbitrary weighting scheme.

The entire weighting process, from the computation of Shannon and Wen entropies to their combination via φ relies exclusively on the observed data in the decision matrix. No subjective scores or pre-assigned preferences are introduced, making the approach: Objective: weights are a direct mathematical outcome of the dataset. Adaptive: the system automatically adjusts to the characteristics of new datasets. Reproducible: any analyst using the same data will obtain identical weights.

This data-driven nature strengthens the credibility of the shelter ranking results, as the model is grounded in quantifiable evidence rather than in potentially inconsistent human judgments.

Chapter 4

Results

4.1 Application of the Model

This methodological framework is applied to a case study of emergency shelters in Manitoba, Canada, using local hotels as shelter alternatives. Criteria relevant to shelter suitability, such as accessibility, safety, and capacity, were defined in collaboration with Emergency Management Organizations (EMO). By applying the mixed weighting model with TOPSIS, this study provides a structured and unbiased approach for ranking shelters, facilitating informed decision-making during emergency evacuations.

4.2 Case study

The case study for this research is based on data provided by the Emergency Management Organization (EMO) of Manitoba, ensuring the practical relevance and applicability of the model to real-world disaster response planning. Manitoba is selected as the geographical focus due to its vulnerability to natural hazards such as floods and wildfires, which frequently lead to the evacuation of affected communities.

In this study, hotels located across Manitoba are considered as potential emergency shelters. This choice reflects the province's existing emergency strategies, where hotels are often utilized to accommodate displaced individuals due to their available infrastructure, accessibility, and existing services. By evaluating hotels as shelter alternatives, the model aligns with current emergency protocols while also offering a structured decision-making framework for optimizing shelter selection.

The integration of EMO’s data ensures that the criteria and decision-making factors used in the model reflect actual needs and operational priorities, allowing for more effective and realistic shelter allocation in times of crisis.

Alternatives are:

Table 4-1: List of Alternatives

#	Alternatives
1	Alt Hotel Winnipeg
2	Holiday Inn Winnipeg-Airport West, an IHG Hotel
3	Victoria Inn Hotel and Convention Centre Winnipeg
4	Radisson Hotel Winnipeg Downtown
5	Lakeview Signature, Trademark Collection by Wyndham
6	Delta Hotels by Marriott Winnipeg
7	Humphry Inn & Suites
8	Hyatt House Winnipeg-South/Outlet Collection
9	Best Western Premier Winnipeg East
10	The Fairmont Winnipeg
11	Clarion Hotel & Suites
12	Canad Inns Destination Centre Polo Park
13	Comfort Inn South
14	Travelodge by Wyndham Winnipeg East
15	Best Western Plus Winnipeg West
16	The Grand Winnipeg Airport Hotel by Lakeview
17	Sandman Hotel & Suites Winnipeg Airport
18	The Fort Garry Hotel, Spa and Conference Centre, Ascend Hotel Collection
19	Assiniboine Gordon Inn on the Park
20	Travelodge by Wyndham Winnipeg
21	Canad Inns Destination Centre Club Regent Casino Hotel
22	Inn At The Forks
23	Super 8 by Wyndham Winnipeg West
24	Super 8 by Wyndham Winnipeg East MB
25	Norwood Hotel
26	Mere Hotel
27	Best Western Plus Pembina Inn & Suites
28	Canad Inns Destination Centre Fort Garry

4.3 Results

To integrate binary and semi-binary criteria into the entropy-based weighting system, each "Yes" or "No" response was numerically encoded. Specifically, a value of 10 was assigned to "Yes", and a value of 1 to "No." This approach ensures meaningful differentiation between alternatives during normalization, particularly when using the Wen entropy method.

The rationale for this choice lies in the need to avoid distortion in the entropy calculation due to lack of variation. Using commonly accepted binary encodings like 1 and 0 could compress entropy values toward zero, reducing the ability of the weighting model to distinguish among criteria. By widening the gap between the two categories (1 vs. 10), the method emphasizes the presence of a desirable attribute ("Yes") while maintaining computational consistency with quantitative criteria. This encoding does not imply absolute magnitudes but provides a structured way to represent the qualitative advantage of satisfying a given criterion within the entropy-based framework.

Proximity to Airport is included as a binary criterion to assess the ease of emergency logistics, supply chain access, and intercity/international evacuation potential. Based on existing literature, a threshold of 6 kilometers is used to determine whether a hotel could be considered “close” to the airport.

Hotels located within 6 km of Winnipeg James Armstrong Richardson International Airport were coded as “Yes”, while others were marked “No”. This classification is consistent with distance-based zoning used in health, urban planning, and transport studies. For example, studies assessing environmental and health impacts of airports often define proximity thresholds between 5 to 8 kmto classify affected zones (Kanaroglou et al., 2009). Similarly, wellbeing analyses in England show that perceived quality of life is affected significantly within a few kilometers of airports (Weinhold & Gatzweiler, 2016). Planning documents and property valuation research also employ 6–10 km airport buffer zones to evaluate zoning and infrastructure policies (Stępień & Nowak, 2020).

Table 4-2: Data Table

Data Table	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
A1	No	Yes	No	Yes	No	No	Yes	No	Yes	Yes	No	No	No	Yes	160	1.2	No	Yes	0.5	Yes	Yes	0.2	Yes	Yes
A2	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	226	5	Yes	Yes	4.5	Yes	Yes	0.3	Yes	Yes
A3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	260	4.8	Yes	Yes	4.5	Yes	Yes	0.4	Yes	Yes
A4	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	263	1	No	Yes	0.8	Yes	Yes	0.1	Yes	Yes
A5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	139	5.5	Yes	Yes	5	Yes	Yes	0.5	Yes	Yes
A6	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	393	1.2	Yes	Yes	1	Yes	Yes	0.2	Yes	Yes
A7	No	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	128	1.5	No	Yes	1.2	Yes	Yes	0.3	Yes	Yes
A8	no	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	135	7	Yes	Yes	6.5	Yes	Yes	0.4	Yes	Yes
A9	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	126	6.8	Yes	Yes	6.5	Yes	Yes	0.5	Yes	Yes
A10	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	340	0.9	No	Yes	0.7	Yes	Yes	0.1	Yes	Yes
A11	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	139	4.5	Yes	Yes	4.2	Yes	Yes	0.3	Yes	Yes
A12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	107	4.2	Yes	Yes	4	Yes	Yes	0.4	Yes	Yes
A13	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	83	8	Yes	Yes	7.5	Yes	Yes	0.5	Yes	Yes
A14	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	75	7.5	Yes	Yes	7.2	Yes	Yes	0.4	Yes	Yes
A15	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	110	4.8	No	Yes	5.8	Yes	Yes	0.2	Yes	Yes
A16	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	101	10.1	No	Yes	3.5	Yes	Yes	0.35	Yes	Yes
A17	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	210	7.7	No	Yes	2.9	Yes	Yes	0.55	Yes	Yes
A18	Yes	Yes	No	Yes	No	Yes	Yes	yes	Yes	Yes	Yes	No	No	Yes	240	2.5	No	Yes	0.6	Yes	Yes	0.06	Yes	Yes
A19	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	50	4.4	Yes	Yes	5.1	Yes	Yes	0.01	Yes	Yes
A20	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	72	6.7	No	Yes	6	Yes	Yes	0.3	Yes	Yes
A21	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	146	5.4	Yes	Yes	3.2	Yes	Yes	0.3	Yes	Yes
A22	Yes	Yes	No	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes	No	No	Yes	116	1.4	No	Yes	2.4	Yes	Yes	0.2	Yes	Yes
A23	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	65	3.3	No	Yes	4.7	Yes	Yes	0.09	Yes	Yes
A24	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	110	8.2	Yes	Yes	5.6	Yes	Yes	0.3	Yes	Yes
A25	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	52	0.65	No	Yes	2	Yes	Yes	0.3	Yes	Yes
A26	Yes	No	No	Yes	No	Yes	Yes	yes	Yes	No	No	No	No	Yes	67	2.6	No	Yes	1.8	Yes	Yes	0.05	Yes	no

A27	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	104	2.5	Yes	Yes	3.9	Yes	Yes	0.1	Yes	Yes
A28	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	106	2.1	No	Yes	4.3	Yes	Yes	0.1	Yes	Yes

Table 4-3: Matrix D

Matrix D	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
A1	1	10	1	10	1	1	10	1	10	10	1	1	1	10	160	1.2	1	10	0.5	10	10	0.2	10	10
A2	1	10	10	10	10	10	10	1	10	10	10	1	1	10	226	5	10	10	4.5	10	10	0.3	10	10
A3	10	10	10	10	10	10	10	10	10	10	10	1	1	10	260	4.8	10	10	4.5	10	10	0.4	10	10
A4	10	10	1	10	1	10	10	1	10	10	10	1	1	10	263	1	1	10	0.8	10	10	0.1	10	10
A5	10	10	10	10	10	10	10	1	10	10	10	1	1	10	139	5.5	10	10	5	10	10	0.5	10	10
A6	1	10	1	10	1	10	10	1	10	10	10	1	1	10	393	1.2	10	10	1	10	10	0.2	10	10
A7	1	1	1	10	10	10	10	1	10	10	10	1	1	10	128	1.5	1	10	1.2	10	10	0.3	10	10
A8	1	10	1	10	10	10	10	1	10	10	10	1	1	10	135	7	10	10	6.5	10	10	0.4	10	10
A9	10	10	1	10	10	10	10	10	10	10	10	1	1	10	126	6.8	10	10	6.5	10	10	0.5	10	10
A10	10	10	1	10	10	10	10	1	10	10	10	1	1	10	340	0.9	1	10	0.7	10	10	0.1	10	10
A11	10	10	1	10	10	10	10	10	10	10	10	1	1	10	139	4.5	10	10	4.2	10	10	0.3	10	10
A12	10	10	10	10	10	10	10	10	10	10	10	1	1	10	107	4.2	10	10	4	10	10	0.4	10	10
A13	10	1	1	10	10	10	10	10	10	10	10	1	1	10	83	8	10	10	7.5	10	10	0.5	10	10
A14	10	10	1	10	10	10	10	10	10	10	10	1	1	10	75	7.5	10	10	7.2	10	10	0.4	10	10
A15	10	10	1	10	10	10	10	1	10	10	10	1	1	10	110	4.8	1	10	5.8	10	10	0.2	10	10
A16	1	10	10	10	10	10	10	1	10	10	10	1	1	10	101	10.1	1	10	3.5	10	10	0.35	10	10
A17	10	10	10	10	10	1	10	10	10	10	10	1	1	10	210	7.7	1	10	2.9	10	10	0.55	10	10
A18	10	10	1	10	1	10	10	10	10	10	10	1	1	10	240	2.5	1	10	0.6	10	10	0.06	10	10
A19	1	10	1	10	10	10	10	1	10	10	10	1	1	10	50	4.4	10	10	5.1	10	10	0.01	10	10
A20	10	10	1	10	10	10	10	10	10	10	10	1	1	10	72	6.7	1	10	6	10	10	0.3	10	10
A21	1	10	1	10	10	10	10	1	10	10	10	1	1	10	146	5.4	10	10	3.2	10	10	0.3	10	10
A22	10	10	1	10	10	10	10	1	10	10	10	1	1	10	116	1.4	1	10	2.4	10	10	0.2	10	10
A23	10	10	1	10	10	10	10	10	10	10	10	1	1	10	65	3.3	1	10	4.7	10	10	0.09	10	10

A24	10	10	1	10	10	10	10	10	10	10	10	1	1	10	110	8.2	10	10	5.6	10	10	0.3	10	10
A25	10	10	1	10	10	10	10	1	10	10	10	1	1	10	52	0.65	1	10	2	10	10	0.3	10	10
A26	10	1	1	10	1	10	10	10	10	1	1	1	1	10	67	2.6	1	10	1.8	10	10	0.05	10	1
A27	1	10	1	10	10	10	10	1	10	10	10	1	1	10	104	2.5	10	10	3.9	10	10	0.1	10	10
A28	10	10	1	10	10	10	10	10	10	10	10	1	1	10	106	2.1	1	10	4.3	10	10	0.1	10	10

4.3.1 Shannon Entropy

This section presents the calculation of objective weights using Shannon's entropy method. Shannon entropy evaluates the variability and informational content of each criterion in the decision matrix. A higher variability indicates greater influence in distinguishing among alternatives. Through normalization, entropy value computation, and a final diversification adjustment, this method assigns objective weights that reduce subjectivity and ensure a data-driven basis for decision-making.

Table 4-4: Matrix R

R	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
A1	0.005	0.040	0.012	0.036	0.004	0.004	0.036	0.007	0.036	0.037	0.004	0.036	0.036	0.036	0.039	0.010	0.006	0.036	0.005	0.036	0.036	0.027	0.036	0.037
A2	0.005	0.040	0.122	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.055	0.041	0.065	0.036	0.042	0.036	0.036	0.040	0.036	0.037
A3	0.050	0.040	0.122	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.063	0.040	0.065	0.036	0.042	0.036	0.036	0.053	0.036	0.037
A4	0.050	0.040	0.012	0.036	0.004	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.064	0.008	0.006	0.036	0.008	0.036	0.036	0.013	0.036	0.037
A5	0.050	0.040	0.122	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.034	0.045	0.065	0.036	0.047	0.036	0.036	0.067	0.036	0.037
A6	0.005	0.040	0.012	0.036	0.004	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.095	0.010	0.065	0.036	0.009	0.036	0.036	0.027	0.036	0.037
A7	0.005	0.004	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.031	0.012	0.006	0.036	0.011	0.036	0.036	0.040	0.036	0.037
A8	0.005	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.033	0.058	0.065	0.036	0.061	0.036	0.036	0.053	0.036	0.037
A9	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.031	0.056	0.065	0.036	0.061	0.036	0.036	0.067	0.036	0.037
A10	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.082	0.007	0.006	0.036	0.007	0.036	0.036	0.013	0.036	0.037
A11	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.034	0.037	0.065	0.036	0.040	0.036	0.036	0.040	0.036	0.037

A12	0.050	0.040	0.122	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.026	0.035	0.065	0.036	0.038	0.036	0.036	0.053	0.036	0.037
A13	0.050	0.004	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.020	0.066	0.065	0.036	0.071	0.036	0.036	0.067	0.036	0.037
A14	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.018	0.062	0.065	0.036	0.068	0.036	0.036	0.053	0.036	0.037
A15	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.027	0.040	0.006	0.036	0.055	0.036	0.036	0.027	0.036	0.037
A16	0.005	0.040	0.122	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.024	0.083	0.006	0.036	0.033	0.036	0.036	0.047	0.036	0.037
A17	0.050	0.040	0.122	0.036	0.043	0.004	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.051	0.063	0.006	0.036	0.027	0.036	0.036	0.073	0.036	0.037
A18	0.050	0.040	0.012	0.036	0.004	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.058	0.021	0.006	0.036	0.006	0.036	0.036	0.008	0.036	0.037
A19	0.005	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.012	0.036	0.065	0.036	0.048	0.036	0.036	0.001	0.036	0.037
A20	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.017	0.055	0.006	0.036	0.057	0.036	0.036	0.040	0.036	0.037
A21	0.005	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.035	0.044	0.065	0.036	0.030	0.036	0.036	0.040	0.036	0.037
A22	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.028	0.012	0.006	0.036	0.023	0.036	0.036	0.027	0.036	0.037
A23	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.016	0.027	0.006	0.036	0.044	0.036	0.036	0.012	0.036	0.037
A24	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.027	0.068	0.065	0.036	0.053	0.036	0.036	0.040	0.036	0.037
A25	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.013	0.005	0.006	0.036	0.019	0.036	0.036	0.040	0.036	0.037
A26	0.050	0.004	0.012	0.036	0.004	0.038	0.036	0.069	0.036	0.004	0.004	0.036	0.036	0.036	0.016	0.021	0.006	0.036	0.017	0.036	0.036	0.007	0.036	0.004
A27	0.005	0.040	0.012	0.036	0.043	0.038	0.036	0.007	0.036	0.037	0.038	0.036	0.036	0.036	0.025	0.021	0.065	0.036	0.037	0.036	0.036	0.013	0.036	0.037
A28	0.050	0.040	0.012	0.036	0.043	0.038	0.036	0.069	0.036	0.037	0.038	0.036	0.036	0.036	0.026	0.017	0.006	0.036	0.041	0.036	0.036	0.013	0.036	0.037

The constant K = 1 ÷ LN (28) ≈ 0.3001 is used to normalize the entropy values, ensuring they fall within a 0 to 1 range. It adjusts the scale of the entropy calculation so that results remain interpretable and consistent. The number 28 in the formula represents the total number of alternatives (in this case, 28 shelters), meaning the constant is directly tied to the number of rows in the decision matrix. A higher number of alternatives results in a smaller K value, helping balance the sensitivity of the entropy scores.

The entropy value for each criterion reflects how uniformly the data is distributed across all alternatives. If the values under a specific criterion are very similar among all shelters, that criterion has high entropy, meaning it doesn't contribute much in distinguishing between alternatives. Conversely, a low entropy value indicates high variability, which makes the criterion more informative and useful for the decision-making process.

Table 4-5: Shanon Entropy Weight

Criteria	**E**	**D**	**Shannon Entropy Weights**	**Criteria**	**E**	**D**	**Shannon Entropy Weights**
C_1	0.92	0.07	0.087	C_{13}	1	0	0
C_2	0.97	0.02	0.027	C_{14}	1	0	0
C_3	0.81	0.18	0.225	C_{15}	0.95	0.04	0.054
C_4	1	0	0	C_{16}	0.94	0.05	0.072
C_5	0.96	0.03	0.046	C_{17}	0.88	0.11	0.143
C_6	0.98	0.01	0.018	C_{18}	1	0	0
C_7	1	0	0	C_{19}	0.94	0.05	0.064
C_8	0.87	0.12	0.155	C_{20}	1	0	0
C_9	1	0	0	C_{21}	1	0	0
C_{10}	0.99	0	0.008	C_{22}	0.94	0.05	0.067
C_{11}	0.98	0.01	0.018	C_{23}	1	0	0
C_{12}	1	0	0	C_{24}	0.99	0	0.008

Weights are assigned to each criterion based on their diversification levels. Criteria that show more variability (and therefore provide more decision-relevant information) receive higher weights. These weights are normalized so they sum up to 1, ensuring a balanced and proportionate influence of each criterion in the final shelter ranking. Next, the entropy-based method proposed by Wen et al. (1998) is employed to calculate another set of objective weights. This approach introduces a mapping function that captures the centrality and spread of each criterion's values, accounting for their significance in a more refined way. The methodology involves benefit/cost normalization, indicator sums, entropy mapping, and normalization of resulting entropy values into weights, providing an alternative weighting system complementary to Shannon's entropy.

4.3.2 Wen Entropy

Table 4-6: Matrix F

Matrix F	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
A1	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.32	0.94	0.00	0.00	0.00	0.00	0.00	0.65	0.00	1.00
A2	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.51	0.54	1.00	0.00	0.57	0.00	0.00	0.46	0.00	1.00
A3	1.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.61	0.56	1.00	0.00	0.57	0.00	0.00	0.28	0.00	1.00
A4	1.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.62	0.96	0.00	0.00	0.04	0.00	0.00	0.83	0.00	1.00
A5	1.00	1.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.26	0.49	1.00	0.00	0.64	0.00	0.00	0.09	0.00	1.00
A6	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	0.94	1.00	0.00	0.07	0.00	0.00	0.65	0.00	1.00
A7	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.23	0.91	0.00	0.00	0.10	0.00	0.00	0.46	0.00	1.00
A8	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.25	0.33	1.00	0.00	0.86	0.00	0.00	0.28	0.00	1.00
A9	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.22	0.35	1.00	0.00	0.86	0.00	0.00	0.09	0.00	1.00
A10	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.85	0.97	0.00	0.00	0.03	0.00	0.00	0.83	0.00	1.00
A11	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.26	0.59	1.00	0.00	0.53	0.00	0.00	0.46	0.00	1.00
A12	1.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.17	0.62	1.00	0.00	0.50	0.00	0.00	0.28	0.00	1.00
A13	1.00	0.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.10	0.22	1.00	0.00	1.00	0.00	0.00	0.09	0.00	1.00
A14	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.07	0.28	1.00	0.00	0.96	0.00	0.00	0.28	0.00	1.00
A15	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.17	0.56	0.00	0.00	0.76	0.00	0.00	0.65	0.00	1.00
A16	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.43	0.00	0.00	0.37	0.00	1.00
A17	1.00	1.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.47	0.25	0.00	0.00	0.34	0.00	0.00	0.00	0.00	1.00
A18	1.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.55	0.80	0.00	0.00	0.01	0.00	0.00	0.91	0.00	1.00
A19	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.60	1.00	0.00	0.66	0.00	0.00	1.00	0.00	1.00
A20	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.06	0.36	0.00	0.00	0.79	0.00	0.00	0.46	0.00	1.00
A21	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.28	0.50	1.00	0.00	0.39	0.00	0.00	0.46	0.00	1.00
A22	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.19	0.92	0.00	0.00	0.27	0.00	0.00	0.65	0.00	1.00
A23	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.04	0.72	0.00	0.00	0.60	0.00	0.00	0.85	0.00	1.00
A24	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.17	0.20	1.00	0.00	0.73	0.00	0.00	0.46	0.00	1.00

A25	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.01	1.00	0.00	0.00	0.21	0.00	0.00	0.46	0.00	1.00
A26	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.79	0.00	0.00	0.19	0.00	0.00	0.93	0.00	0.00
A27	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.16	0.80	1.00	0.00	0.49	0.00	0.00	0.83	0.00	1.00
A28	1.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.16	0.85	0.00	0.00	0.54	0.00	0.00	0.83	0.00	1.00

The D value represents the total score of a criterion across all alternatives after normalization. It serves as a baseline for comparing individual shelter values under that criterion. By calculating the total, the model can understand how each alternative's value relates proportionally to the whole, which is essential for the entropy mapping step that follows.

The constant K is used to scale the entropy calculation in the Wen method. The value 0.64872 comes from the maximum of the mapping function used in Wen entropy, and 28 is the number of alternatives. This scaling ensures that the resulting entropy values stay within a meaningful and comparable range. It essentially adjusts the calculation to reflect the specific size of the dataset and the behavior of the mapping function, allowing for fair comparisons between criteria.

The e value for each criterion is the entropy calculated using Wen's non-linear mapping function. This function gives more nuanced attention to values around the middle of the distribution (near 0.5) and helps capture both balance and imbalance in how alternatives are scored. A high **e** means that the criterion has less ability to distinguish between shelters (it's less informative), while a low e indicates greater contrast and more decision-making value.

Table 4-7: Wen Entropy Weight

Criteria	D	e	Wen Entropy Weights	Criteria	D	e	Wen Entropy Weights
C_1	19	0.140	0.039	C_{13}	0	0	0
C_2	25	0.142	0.038	C_{14}	0	0	0
C_3	6	0.121	0.039	C_{15}	7.93	0.138	0.039
C_4	0	0	0	C_{16}	10.92	0.140	0.039
C_5	23	0.142	0.038	C_{17}	14	0.137	0.039
C_6	26	0.142	0.038	C_{18}	0	0	0
C_7	0	0	0	C_{19}	13.12	0.149	0.039
C_8	13	0.136	0.039	C_{20}	0	0	0
C_9	0	0	0	C_{21}	0	0	0
C_{10}	27	0.143	0.038	C_{22}	14.61	0.141	0.038
C_{11}	26	0.142	0.038	C_{23}	0	0	0
C_{12}	0	0	0	C_{24}	27	0.143	0.038

The W value is the final weight assigned to each criterion based on its mapped entropy. Criteria that showed more variability and better ability to differentiate between alternatives (i.e., lower e) are assigned higher weights. These weights are normalized so they add up to 1, ensuring each criterion contributes proportionately to the final ranking of shelters. The Wen method, therefore, gives a refined and balanced assessment of each criterion’s importance.

4.3.3 Hybrid Weighting

To benefit from the strengths of both Shannon and Wen entropy, a hybrid weighting scheme is introduced. This model integrates the two sets of objective weights through mixing parameters ϕ and λ, allowing for flexible adjustment between the two methods. The resulting combined weights offer a balanced reflection of both information content and practical importance, enhancing robustness in the final shelter ranking process. This dual-weight strategy is novel in the context of emergency shelter selection and supports a more comprehensive evaluation.

Table 4-8: Hybrid Weighting Matrix

φ	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
φ=0	0.039	0.039	0.040	0.000	0.039	0.039	0.000	0.039	0.000	0.039	0.039	0.000	0.000	0.000	0.039	0.039	0.039	0.000	0.039	0.000	0.000	0.039	0.000	0.039
φ=0.1	0.044	0.038	0.058	0.000	0.040	0.037	0.000	0.051	0.000	0.036	0.037	0.000	0.000	0.000	0.041	0.042	0.050	0.000	0.042	0.000	0.000	0.042	0.000	0.036
φ=0.2	0.049	0.037	0.077	0.000	0.040	0.035	0.000	0.062	0.000	0.033	0.035	0.000	0.000	0.000	0.042	0.046	0.060	0.000	0.044	0.000	0.000	0.045	0.000	0.033
φ=0.3	0.054	0.035	0.096	0.000	0.041	0.033	0.000	0.074	0.000	0.030	0.033	0.000	0.000	0.000	0.044	0.049	0.071	0.000	0.047	0.000	0.000	0.047	0.000	0.030
φ=0.4	0.059	0.034	0.114	0.000	0.042	0.031	0.000	0.086	0.000	0.027	0.031	0.000	0.000	0.000	0.045	0.052	0.081	0.000	0.049	0.000	0.000	0.050	0.000	0.027
φ=0.5	0.063	0.033	0.133	0.000	0.043	0.028	0.000	0.097	0.000	0.024	0.028	0.000	0.000	0.000	0.047	0.056	0.091	0.000	0.052	0.000	0.000	0.053	0.000	0.024
φ=0.6	0.068	0.032	0.151	0.000	0.044	0.026	0.000	0.109	0.000	0.021	0.026	0.000	0.000	0.000	0.048	0.059	0.102	0.000	0.055	0.000	0.000	0.056	0.000	0.021
φ=0.7	0.073	0.031	0.170	0.000	0.044	0.024	0.000	0.120	0.000	0.018	0.024	0.000	0.000	0.000	0.050	0.063	0.112	0.000	0.057	0.000	0.000	0.059	0.000	0.018
φ=0.8	0.078	0.030	0.189	0.000	0.045	0.022	0.000	0.132	0.000	0.015	0.022	0.000	0.000	0.000	0.051	0.066	0.123	0.000	0.060	0.000	0.000	0.061	0.000	0.015
φ=0.9	0.083	0.029	0.207	0.000	0.046	0.020	0.000	0.144	0.000	0.012	0.020	0.000	0.000	0.000	0.053	0.069	0.133	0.000	0.062	0.000	0.000	0.064	0.000	0.012
φ=1	0.088	0.027	0.226	0.000	0.047	0.018	0.000	0.155	0.000	0.009	0.018	0.000	0.000	0.000	0.054	0.073	0.144	0.000	0.065	0.000	0.000	0.067	0.000	0.009

4.3.4 TOPSIS-Based Shelter Ranking

This section applies the TOPSIS method to rank emergency shelter alternatives based on their proximity to ideal and anti-ideal solutions. Using the mixed weights derived in the previous step, the normalized decision matrix is transformed into a weighted matrix. Euclidean distances to ideal and anti-ideal points are calculated for each alternative, followed by the computation of relative closeness values. The final ranking reflects each shelter's suitability in supporting evacuees during a natural disaster scenario, ensuring the selected options are both practical and resilient.

Table 4-9: Final Shelter Ranking

Alternatives	$\Phi = 0$	$\Phi = 0.1$	$\Phi = 0.2$	$\Phi = 0.3$	$\Phi = 0.4$	$\Phi = 0.5$	$\Phi = 0.6$	$\Phi = 0.7$	$\Phi = 0.8$	$\Phi = 0.9$	$\Phi = 1$
A_1	28	28	28	28	27	27	27	27	27	27	27
A_2	3	3	3	2	3	3	3	3	3	3	3
A_3	1	1	1	1	1	1	1	1	1	1	1
A_4	16	19	20	21	21	21	23	23	23	23	23
A_5	4	4	4	4	4	4	4	4	4	5	5
A_6	8	10	14	15	15	15	15	16	16	16	17
A_7	27	27	27	27	28	28	28	28	28	28	28
A_8	22	23	23	22	22	22	21	21	21	20	20
A_9	13	13	11	10	10	10	9	9	9	9	9
A_{10}	7	14	16	16	20	20	20	20	20	24	22
A_{11}	5	6	7	7	7	7	7	7	7	7	7
A_{12}	2	2	2	2	2	2	2	2	2	2	2
A_{13}	21	17	15	12	11	11	11	11	11	11	11
A_{14}	14	12	10	8	8	8	8	8	8	8	8
A_{15}	20	22	24	25	25	26	26	26	26	26	26
A_{16}	25	15	6	6	6	6	6	6	6	6	6
A_{17}	11	5	5	5	5	5	5	5	5	4	4
A_{18}	9	9	12	13	13	13	13	13	13	13	13
A_{19}	17	18	18	18	19	19	19	19	19	19	19
A_{20}	18	20	19	19	16	17	17	17	17	17	16
A_{21}	23	24	25	24	23	23	22	22	22	22	21
A_{22}	19	21	22	26	24	24	24	24	24	24	24
A_{23}	10	11	13	12	14	14	14	14	14	14	14
A_{24}	12	8	9	9	9	9	10	10	10	10	10
A_{25}	24	26	26	20	26	25	25	25	25	25	25
A_{26}	26	25	21	24	18	16	16	16	15	15	15
A_{27}	15	16	17	17	17	18	18	18	18	18	28
A_{28}	6	7	8	11	12	12	12	12	12	12	12

The final ranking table was generated by applying TOPSIS model to a set of alternatives (hotels in Winnipeg) under a hybrid objective weighting scheme that combines Shannon entropy and Wen entropy. The primary purpose of integrating these two entropy methods was to appropriately account for both quantitative and binary/semi-binary criteria in the shelter evaluation framework. While Shannon entropy is well-suited for continuous or numerical data, Wen entropy was implemented to better handle criteria expressed as binary “yes/no” evaluations by using weighted divergence measures. To merge these two objective weighting schemes, a parameterized blending approach was adopted.

The blending mechanism introduces a parameter φ (phi), where φ ranges from 0 to 1. The value of φ determines the influence of each entropy method on the final weight of each criterion.

Here, when φ = 0, the final weights are entirely based on Shannon entropy, and when φ = 1, the model relies fully on Wen entropy. Intermediate values allow for a gradual shift in the weighting emphasis from quantitative to binary-focused criteria.
After determining the hybrid weights for each φ value, the TOPSIS algorithm was applied to the decision matrix to compute the Relative Closeness (RC) values for each alternative. These RC values were then ranked from highest to lowest, where a higher RC score indicates a more suitable shelter alternative. The table displays the rank positions of each hotel alternative (A1 to A28) under eleven different φ values ranging from 0 to 1 in increments of 0.1.

The ranking table provides a comprehensive view of how each shelter alternative's performance is affected by the choice of weighting strategy. One of the key insights from this table is the stability of certain alternatives regardless of the φ value, which demonstrates their robustness across a range of weighting schemes. For example, Alternative A3 consistently ranks 1st across all φ values, from φ = 0 to φ = 1. This indicates that A3 is a highly desirable alternative under both binary-focused and quantitatively focused evaluations. Similarly, Alternative A12 ranks 2nd throughout, showing equal strength and versatility in terms of the various criteria it satisfies.

Other alternatives display moderate sensitivity to changes in φ. For instance, Alternative A6 begins at rank 8 under φ = 0, drops to rank 17 by φ = 1, and gradually declines through intermediate φ values. This pattern suggests that A6 benefits more from quantitatively weighted criteria (such as room capacity, distance to hospital, etc.) than from binary criteria (such as presence of on-site restaurants or emergency power supply). As the influence of Wen entropy increases (with φ increasing), its relative performance diminishes, indicating that while A6 may score well numerically, it lacks some of the binary features considered important under the Wen entropy model.

Alternatives like A16, which shows a sharp jump from rank 25 at φ = 0 to rank 6 from φ = 0.2 onward, illustrate the opposite behavior. This shift reveals that A16 performs significantly better when binary or semi-binary criteria are given more importance, possibly due to strong attributes like proximity to the airport, accessibility features, or emergency readiness that were encoded in binary form. This reinforces the idea that the Wen entropy method captures meaningful information not adequately represented through purely quantitative weighting systems.

Some alternatives, such as A4 and A10, experience fluctuations in ranking that reflect a nonlinear relationship with φ. For example, A4 moves from rank 16 at $\varphi = 0$ to rank 23 at $\varphi = 1$, showing a continuous decline. In contrast, A10 shifts more irregularly starting strong, then dropping as φ increases. These behaviors suggest that the weighting scheme significantly impacts their perceived utility as shelters, likely due to imbalanced performance across different types of criteria (e.g., scoring well in infrastructure but not in soft services like support for different age groups or pet-friendliness).

The most unstable alternatives are those like A26, A25, and A27, which shift their ranks drastically across φ values, showing no consistent pattern. These alternatives may have unbalanced profiles: strong in a few binary aspects but weak in others or performing moderately across all quantitative criteria without excelling in any. Their sensitivity to φ suggests a lack of overall robustness, and such options may not be ideal for selection in uncertain or dynamic decision environments.

On the other hand, some alternatives maintain moderate yet consistent rankings across the φ spectrum, such as A5, which remains within the top 5 across all values until $\varphi = 0.9$. These alternatives are considered reliably favorable, even if they do not always secure the top rank. They are especially valuable in practical applications where decision-makers prefer stable, well-rounded options over those that depend heavily on one class of criteria.

The extreme ends of the ranking table (e.g., A1 and A7) remain consistently at the bottom. For example, A1 remains in rank 28 through $\varphi = 0.3$ and slightly improves to rank 27 from $\varphi = 0.4$ onward. This consistent low ranking implies that A1 lacks key attributes across both binary and quantitative domains, likely underperforming in capacity, accessibility, proximity, or emergency readiness. This makes it a non-viable shelter regardless of how the weights are assigned.

Finally, the overall structure of the table supports the value of conducting a sensitivity analysis using varying φ values. Decision-makers are often faced with uncertainty regarding which criteria to prioritize in complex, real-world emergency contexts. By exploring a full range of φ values, the model enables a more comprehensive evaluation of each alternative's robustness and responsiveness. It allows identification of “universally strong” shelters (like A3 and A12), and “conditionally strong” shelters (like A16 or A6), which perform well only under certain strategic priorities.

4.4 Sensitivity Analysis

In MCDM, especially when objective weighting techniques are used, sensitivity analysis plays a crucial role in validating the robustness and reliability of the final results. In this study, we adopted a hybrid entropy-based weighting model that combines Shannon entropy and Wen entropy, allowing us to account for both quantitative and binary types of criteria in evaluating emergency shelters. The merging of these two entropy methods is controlled through the adjustable parameter φ (phi), which allows the model to vary the influence of each entropy source in the overall decision-making process.

By performing a sensitivity analysis across a range of φ values from 0 to 1 (in increments of 0.1), we simulate scenarios where the emphasis on either quantitative or binary data shifts gradually. When $\varphi = 0$, the model is entirely driven by Shannon entropy, reflecting the influence of continuous variables like room capacity or proximity to hospitals. At the other extreme, $\varphi = 1$, the weighting scheme is based purely on Wen entropy, highlighting binary criteria such as presence of emergency power supply, accessibility, or pet-friendliness.

The sensitivity analysis, therefore, enables us to answer key questions such as: Which shelter alternatives consistently perform well regardless of weight distribution? Which ones are highly sensitive to how the criteria are weighted? Are the final rankings robust and reliable under varying model assumptions?

The following plots explain these questions by analyzing the ranking behavior of the best, worst, most stable, and most sensitive alternatives across the φ spectrum.

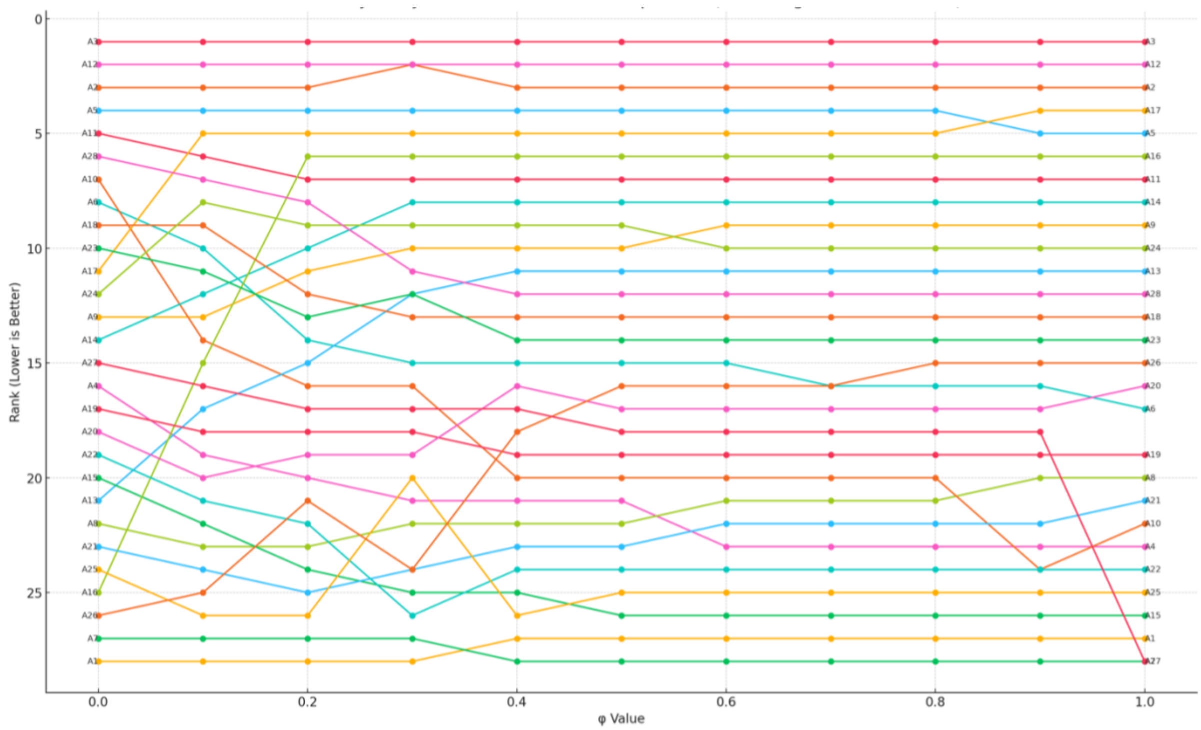

Figure 3: Sensitivity of all alternatives across φ values

From this refined plot, we clearly observe that A3, A12, and A2 remain in the top three ranks across all φ values, demonstrating high robustness. Their consistently excellent performance regardless of how much weight is placed on binary (Wen) or quantitative (Shannon) criteria indicates they offer a well-balanced combination of capacity, amenities, and readiness features. On the other end, A1, A7, and A27 remain anchored near the bottom of the ranking across all φ values. This implies that these alternatives lack sufficient emergency shelter characteristics—such as proximity to hospitals, structural resilience, or critical facilities—regardless of which type of data is prioritized.

This plot offers a holistic visual validation of your hybrid model's behavior.It also supports further discussion on how some hotels are "consistently good" while others are "conditionally better or worse" depending on the weighting.

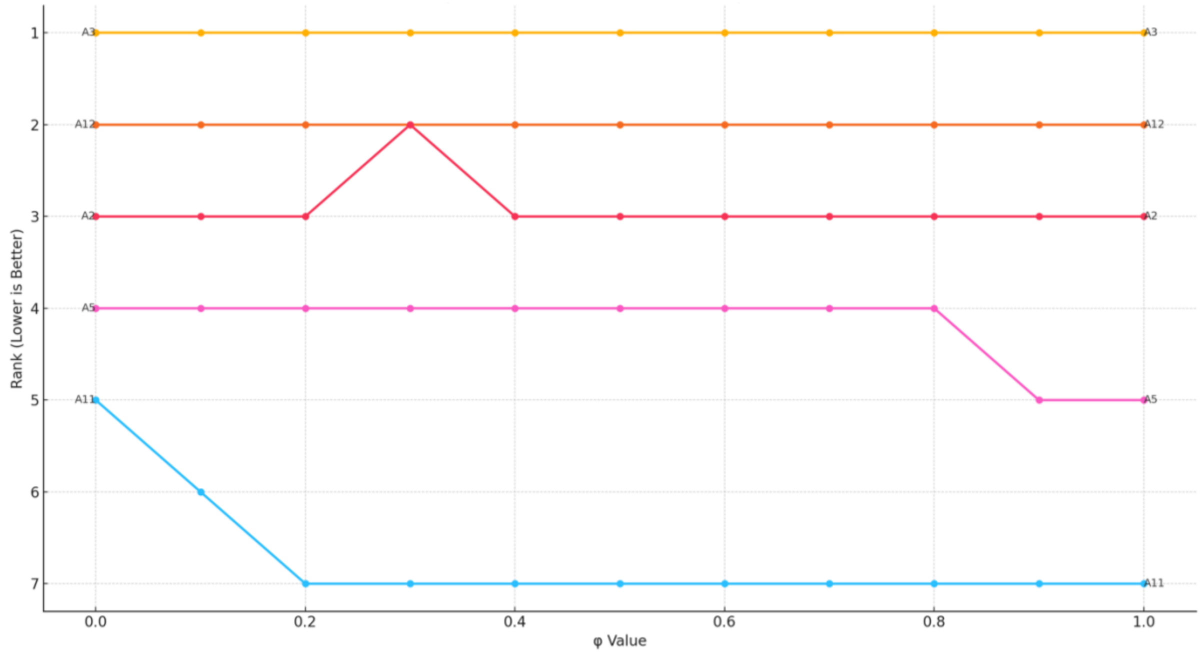

Figure 4: Top ranked alternatives across φ values

This plot shows the ranking trends of A3, A12, A2, A5, and A11, which were the top 5 performers across most φ values. Notably, A3 maintains a perfect 1st rank throughout all φ values, making it a universally best-performing alternative. Similarly, A12 consistently holds the 2nd rank, and A2 stays at or near 3rd. This indicates these hotels have a balanced advantage across both quantitative and binary criteria, making them ideal candidates for emergency shelter selection under almost any decision scenario.

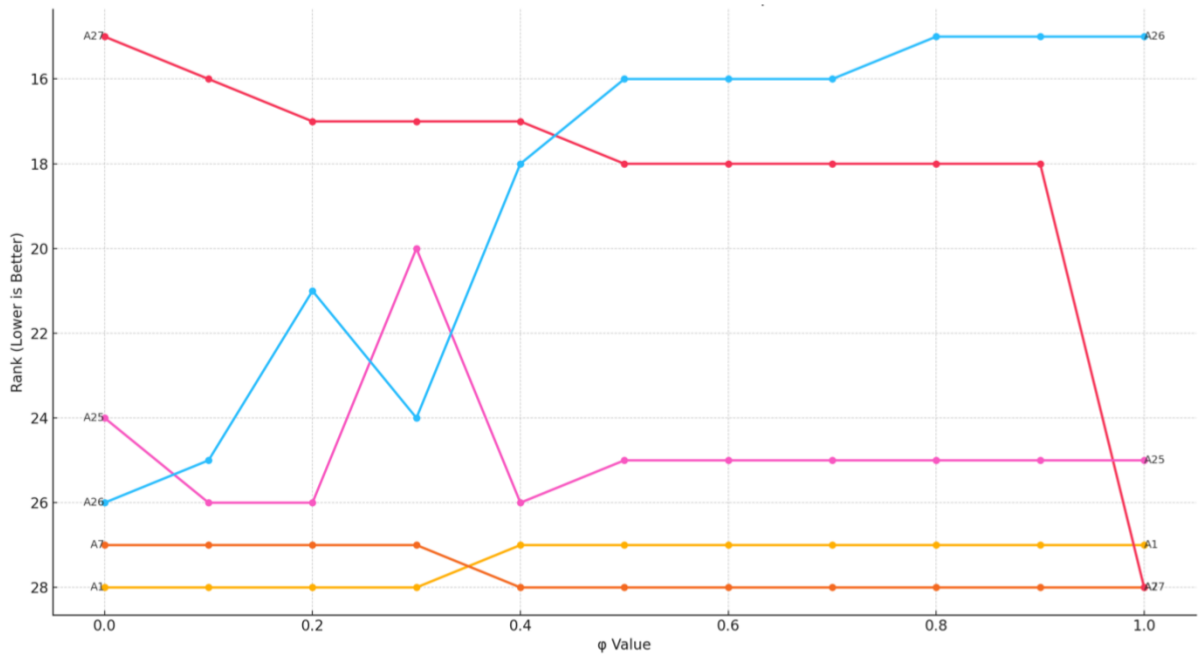

Figure 5: Bottom-ranked alternatives across φ values

This plot focuses on the lowest-performing shelters, specifically A1, A7, A27, A25, and A26. Alternatives A1 and A7 consistently rank 27th and 28th, suggesting that they lack critical infrastructure, accessibility, or service features required in emergency shelter settings.

A26 and A25 show slightly more variation, but they remain clustered in the bottom rankings, indicating weak performance across both types of criteria. These alternatives are not suitable candidates under any configuration of the model and should likely be excluded from emergency preparedness plans.

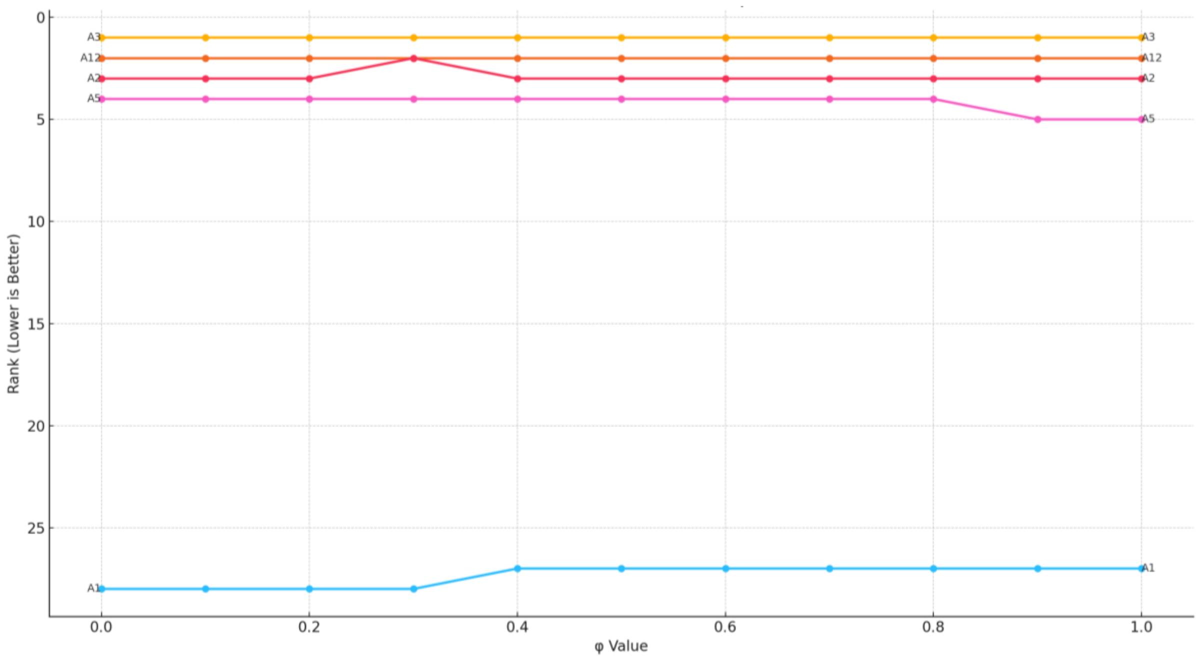

Figure 6: Most stable alternatives across φ values

The alternatives with the lowest standard deviation in ranks across φ values are A3, A12, A2, A5, and A1. Their consistently flat lines in the plot reflect high resilience to changing criteria weightings. Most of these are top ranked (A3, A12, A2, A5), reinforcing their strategic importance. Interestingly, A1 also appears here, despite being among the worst overall. Its stability at the bottom end underscores its lack of competitive criteria regardless of weighting and highlights how stability alone does not imply desirability.

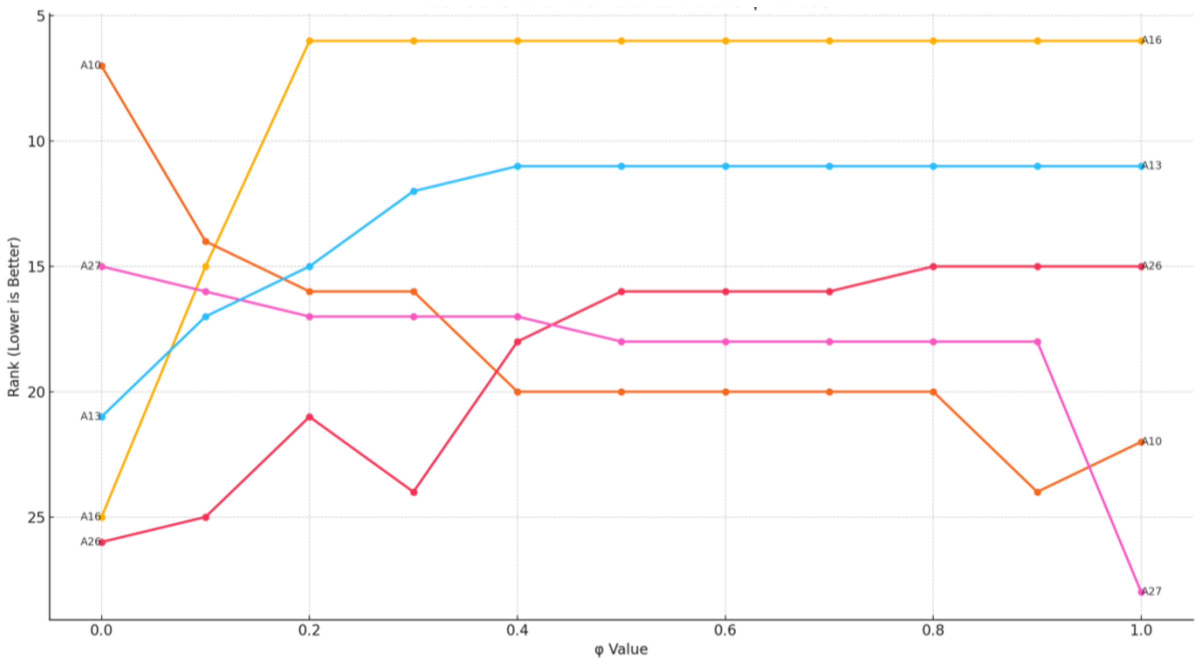

Figure 7: Most sensetive alternatives across φ values

This final plot shows the most φ-sensitive alternatives based on rank standard deviation: A16, A13, A26, A10, and A27. These lines exhibit noticeable fluctuations, reflecting how their rank is highly influenced by which set of criteria is emphasized. For instance, A16 jumps from rank 25 at $\varphi = 0$ to rank 6 at $\varphi = 0.2$ and remains high thereafter, indicating it performs better under binary-focused evaluation. A10 and A27 also show instability, making them conditionally suitable but not consistently reliable across all strategic priorities.

Table 4-10: Sensetivity summary table

Alternative	Standard Deviation	Rank Range	Alternative	Standard Deviation	Rank Range
A3	0.0	0	A18	1.60113596038449	4
A12	0.0	0	A25	1.6787441193290400	6
A2	0.30151134457776400	1	A22	1.9021518914592000	7
A5	0.40451991747794500	1	A17	1.91168654714769	7
A1	0.5045249791095130	1	A15	2.0045403009622500	6
A7	0.5045249791095130	1	A14	2.0714509627092500	6
A11	0.6466697906828630	2	A4	2.2279219832921400	7
A19	0.6875516509523290	2	A28	2.3393860888547800	6
A24	1.026910636104940	4	A6	2.7601053998320100	9
A8	1.0357254813546300	3	A13	3.3601947995479500	10
A21	1.1677484162422800	4	A27	3.400534717310850	13
A20	1.2933395813657300	4	A26	4.3547257506801000	11
A23	1.4459976109624400	4	A10	4.657350007344210	17
A9	1.5374122295716100	4	A16	6.088737740511350	19

The Sensitivity Summary Table presents two key metrics for each shelter alternative (hotel) across the full range of φ values (from 0 to 1), which were used to blend Shannon and Wen entropy weights in the TOPSIS model: Standard Deviation of Ranks that measures how much each alternative's rank fluctuates as φ changes. A standard deviation of 0 means the alternative's rank remained constant across all φ values, indicating maximum stability. Higher standard deviations indicate that the alternative's rank is more sensitive to changes in weight allocation between quantitative and binary criteria. Rank Range that shows the difference between the highest and lowest rank an alternative received across the φ spectrum. It is a simple measure of variability and complements the standard deviation by highlighting how wide the movement is, even if gradual.

From the table, we observe that: Alternatives A3 and A12 have a standard deviation of 0 and a rank range of 0, meaning their ranking never changed regardless of the φ value. This confirms that they are universally optimal and can be confidently recommended regardless of the weighting strategy. Alternative A2 shows very little fluctuation (std ≈ 0.30), with a rank range of just 1. This also indicates high stability. Alternatives like A1 and A5 also exhibit low variability, though A1 is consistently ranked near the bottom, making it a stable but suboptimal alternative.

This table enables decision-makers to differentiate between consistently good and consistently poor performers, and to identify alternatives that may require additional scenario-based analysis due to their ranking volatility.

To assess the robustness of each shelter alternative under varying weighting schemes, we adopted a sensitivity analysis approach consistent with Alinezhad and Amini (2011), who showed that fluctuations in alternative rankings caused by weight changes can be quantified using standard deviation and rank range. Alternatives with minimal variance are considered stable and reliable across decision preferences.

We can now classify the alternatives into interpretive categories using their rank behavior:

Table 4-11: Typology Based on Sensitivity

Alternative	Std. Dev	Rank Range	Avg. Rank	Typology	Recommendation
A3	0.00	0	1.00	Universally Optimal	Strongly Recommended
A12	0.00	0	2.00	Universally Optimal	Strongly Recommended
A2	0.30	1	2.91	Stable High Performer	Safe Choice
A5	0.40	1	4.00	Stable High Performer	Safe Choice
A1	0.50	1	27.00	Stable but Suboptimal	Not Recommended

The typology table presents a concise but powerful summary of how selected alternatives behave across different weighting strategies in the hybrid entropy-TOPSIS model. Each row corresponds to a hotel (alternative), and the columns break down how that hotel performed across all 11 values of the parameter φ, which blends Shannon and Wen entropy weights. Here's how to interpret each column:

Alternative column lists the unique identifier for each hotel that was evaluated as a potential emergency shelter.

Std. Dev (Standard Deviation) column measures the variation in the ranking of each alternative as the φ parameter changes from 0 to 1. A value of 0.00 indicates the hotel held a completely stable rank across all φ values, while higher values indicate that the ranking fluctuated more. The lower the standard deviation, the more robust and predictable the performance of that alternative, regardless of which criteria (binary or quantitative) are emphasized.

Rank Range column is the numerical range between the highest (worst) and lowest (best) rank the alternative received across all φ values. It complements the standard deviation by showing the maximum fluctuation span in rank. Example: A rank range of 1 means the alternative only moved one position up or down, while a larger range indicates it shifted more dramatically.

Avg. Rank column is the average of all rankings the alternative received across φ values. Since TOPSIS ranks alternatives from best (1) to worst (28), a lower average rank indicates overall stronger performance. This helps evaluate whether an alternative was generally a high performer, even if it fluctuated a little. A hotel with an average rank of 2.00 is generally excellent; one with an average of 27.00 is consistently poor.

Each alternative is assigned a qualitative label based on its sensitivity and performance. This classification reflects how stable and useful the alternative is for decision-makers: Universally Optimal: Always ranked at the top and never changed, best possible case. Stable High Performer: Rarely fluctuated and maintained a strong rank. Stable but Suboptimal: Consistently performed poorly but is predictable. Conditionally Optimal (not shown in this table): Performs well only under specific φ values. Highly Sensitive / Unreliable (also not shown here): Highly volatile and hard to rely on.

This is a direct practical conclusion for decision-makers based on the above metrics: Strongly Recommended: Reliable and high-performing regardless of weighting strategy. Safe Choice: Very likely to be a good option under most scenarios. Not Recommended: Weak overall performance, even if stable.

This table translates complex mathematical outputs into strategic, actionable insights. By categorizing alternatives based on both performance and sensitivity, it allows emergency planners to: focus on robust and top-performing options (A3, A12), consider safe fallback options (A2, A5), rule out consistently weak shelters (A1), and make informed decisions that are resilient to uncertainty in prioritizing evaluation criteria.

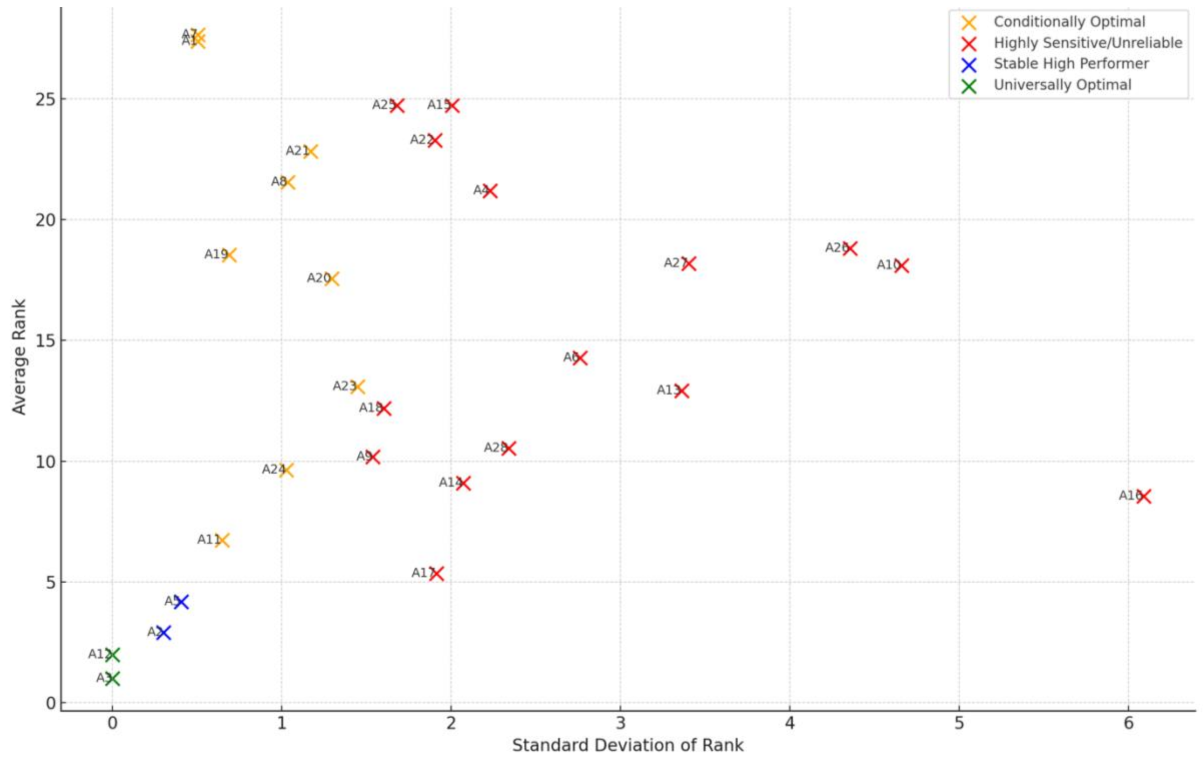

Figure 8: Topology of Alternatives based on sensitivity performance

This scatter plot categorizes all alternatives based on two axes: X-axis: Standard Deviation of Rank (measuring sensitivity to φ), Y-axis: Average Rank (performance, where lower is better).

Each point represents one hotel, colored according to its typology, which reflects how it behaves across all weighting scenarios: Universally Optimal (e.g., A3, A12): Low standard deviation and top average ranks. These are the most reliable and consistently strong alternatives. They are ideal choices regardless of the decision-maker's preference between binary or quantitative criteria. Stable High Performers (e.g., A2, A5, A11): Low variability with good (but not top) average rank. These are safe fallback options, performing well without much sensitivity to entropy balance. Stable but Suboptimal (e.g., A1): These alternatives are consistently ranked poorly, yet show no sensitivity to changing weights. Their performance is predictably low, likely due to missing essential infrastructure or support features. Conditionally Optimal (e.g., A10, A16, A6): Moderate average rank but higher variability. These may perform well under specific scenarios (e.g., when binary criteria dominate), and are strategically valuable in targeted emergency situations. Highly Sensitive / Unreliable (e.g., A26, A27): Large shifts in rank and poor average performance. These options are too inconsistent to be relied on and may require major improvements before inclusion in emergency planning.

This plot is a powerful visual representation of both performance and reliability in one figure. It gives decision-makers a way to prioritize stable and high-performing shelters, understand which options are only useful under specific weighting assumptions, avoid shelters that are unreliable or universally weak.

Table 4-12: RC score plot

Alternatives	Φ = 0	Φ = 0.1	Φ = 0.2	Φ = 0.3	Φ = 0.4	Φ = 0.5	Φ = 0.6	Φ = 0.7	Φ = 0.8	Φ = 0.9	Φ = 1
A_1	0.404	0.367	0.336	0.310	0.290	0.273	0.259	0.248	0.238	0.230	0.224
A_2	0.607	0.612	0.620	0.627	0.634	0.640	0.645	0.649	0.653	0.656	0.659
A_3	0.694	0.715	0.735	0.752	0.766	0.778	0.788	0.797	0.804	0.811	0.816
A_4	0.512	0.461	0.419	0.387	0.361	0.340	0.323	0.310	0.298	0.289	0.281
A_5	0.574	0.587	0.601	0.613	0.623	0.631	0.638	0.644	0.649	0.653	0.657
A_6	0.541	0.495	0.458	0.430	0.408	0.391	0.377	0.367	0.358	0.350	0.344
A_7	0.426	0.381	0.343	0.313	0.289	0.270	0.254	0.242	0.231	0.222	0.215
A_8	0.471	0.429	0.396	0.371	0.353	0.338	0.327	0.319	0.312	0.307	0.302
A_9	0.523	0.494	0.471	0.454	0.441	0.431	0.423	0.417	0.412	0.408	0.405
A_{10}	0.551	0.493	0.448	0.412	0.384	0.362	0.344	0.329	0.316	0.306	0.297
A_{11}	0.556	0.520	0.492	0.471	0.456	0.444	0.435	0.428	0.422	0.418	0.414
A_{12}	0.629	0.657	0.682	0.704	0.722	0.738	0.751	0.762	0.771	0.779	0.786
A_{13}	0.491	0.471	0.454	0.441	0.431	0.423	0.417	0.412	0.408	0.405	0.402
A_{14}	0.521	0.494	0.472	0.455	0.442	0.432	0.425	0.419	0.414	0.410	0.407
A_{15}	0.492	0.437	0.394	0.360	0.333	0.312	0.295	0.281	0.269	0.259	0.251
A_{16}	0.468	0.480	0.494	0.507	0.519	0.528	0.537	0.544	0.550	0.555	0.559
A_{17}	0.532	0.555	0.577	0.595	0.610	0.622	0.632	0.641	0.648	0.654	0.659
A_{18}	0.536	0.495	0.463	0.439	0.420	0.406	0.394	0.385	0.378	0.372	0.367
A_{19}	0.507	0.466	0.433	0.408	0.388	0.373	0.361	0.351	0.343	0.336	0.331
A_{20}	0.495	0.457	0.428	0.406	0.390	0.377	0.367	0.359	0.353	0.348	0.344
A_{21}	0.470	0.426	0.393	0.368	0.349	0.335	0.324	0.316	0.309	0.304	0.300
A_{22}	0.493	0.442	0.400	0.368	0.342	0.322	0.305	0.292	0.281	0.271	0.263
A_{23}	0.535	0.494	0.462	0.438	0.419	0.405	0.393	0.384	0.377	0.371	0.366
A_{24}	0.526	0.495	0.472	0.454	0.441	0.431	0.423	0.417	0.412	0.408	0.405
A_{25}	0.469	0.424	0.387	0.357	0.333	0.314	0.298	0.286	0.275	0.266	0.259
A_{26}	0.429	0.419	0.408	0.398	0.389	0.381	0.375	0.370	0.365	0.361	0.358
A_{27}	0.516	0.471	0.436	0.410	0.389	0.373	0.361	0.351	0.343	0.336	0.331
A_{28}	0.552	0.508	0.473	0.447	0.428	0.412	0.400	0.391	0.383	0.377	0.372

To complement the ranking results and provide a more granular evaluation of each alternative's performance, a detailed table of Relative Closeness (RC) scores is presented. The RC score, a fundamental component of the TOPSIS method, quantifies how close an alternative is to the ideal solution by considering its normalized distance from both the ideal and anti-ideal options. Unlike ordinal rankings that only provide a relative position, RC scores offer a continuous performance metric ranging between 0 and 1, with values closer to 1 indicating greater proximity to the optimal solution.

This table shows the RC values of all 28 hotel alternatives across varying values of the mixing parameter φ (ranging from 0 to 1), which controls the balance between two objective weighting methods: Shannon entropy, capturing information dispersion in continuous data, and Wen entropy, designed to handle crisp or binary criteria with greater sensitivity. By examining how each alternative's RC score responds to changes in φ, decision-makers can identify shelters that consistently perform well across different weight assumptions, thereby improving the robustness and reliability of emergency preparedness plans.

This sensitivity-based RC evaluation not only confirms the stability of top alternatives but also highlights which shelters are particularly dependent on certain types of criteria. This deeper insight is essential in disaster contexts, where flexibility and confidence in selected facilities can significantly influence response effectiveness.

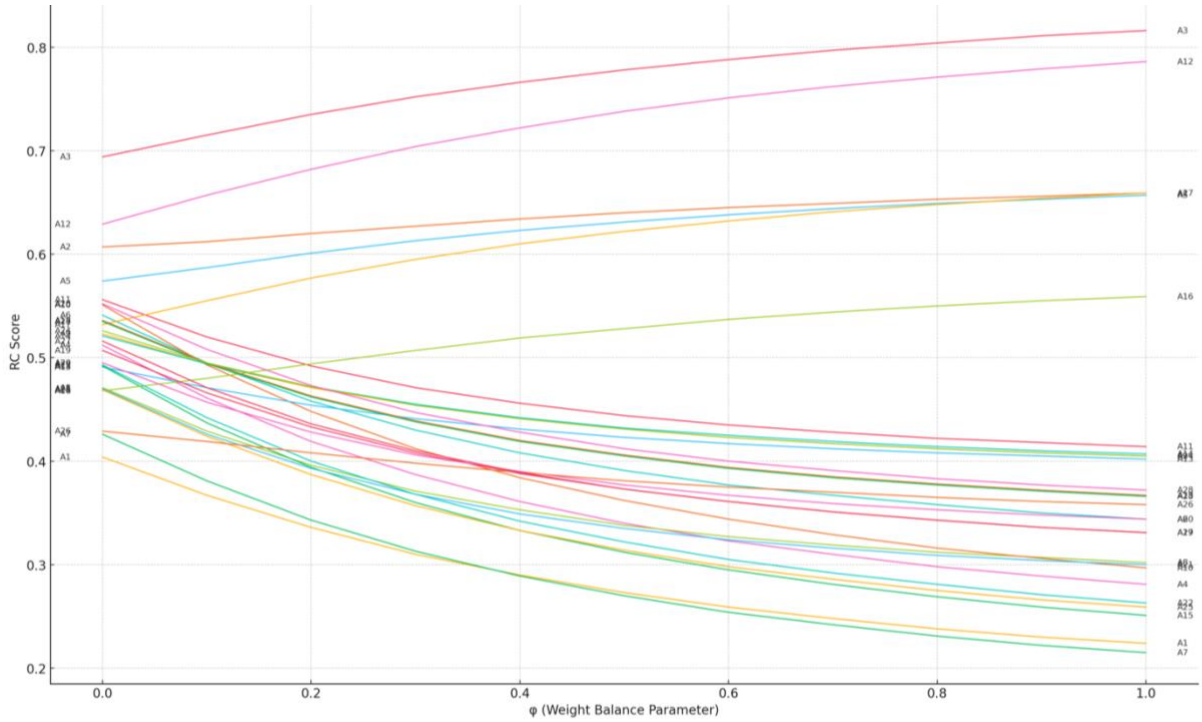

Figure 9: RC Score Trends Across φ Values

The above graph presents a comprehensive sensitivity analysis of RC scores for 28 hotel alternatives across varying values of the parameter φ (phi) in the hybrid Entropy-TOPSIS model. This parameter determines the balance between Shannon entropy (objective weight source) and Wen entropy (adjusted entropy for binary or crisp criteria). The values range from φ = 0 (fully Shannon-based) to φ = 1 (fully Wen-based).

Each line on the plot represents one alternative, and both ends of the line are tagged with the alternative's name to help track the change in performance. The y-axis shows the RC score (between 0 and 1), which reflects how close each alternative is to the ideal solution, the higher the RC score, the better the alternative. The x-axis shows the φ values.

Alternatives like A3 (RC 0.694 → 0.816) and A12 (RC 0.629 → 0.786) consistently outperform others across all φ values. Their RC scores increase smoothly, suggesting that these hotels are strong candidates regardless of whether the weighting favors binary criteria (Wen) or continuous/objective ones (Shannon). These are excellent choices for robust shelter solutions.

Some alternatives, such as A16, show a noticeable upward trend in their RC score as φ increases. For instance, A16's RC increases from 0.468 (φ=0) to 0.559 (φ=1), indicating that it performs better when binary or crisp criteria are given more importance. This implies that A16 might have strong characteristics in those dimensions, such as emergency facilities, accessibility, or safety, which are typically modeled with binary values (yes/no).

Conversely, alternatives such as A1 and A7 see a substantial drop in RC scores as φ increases. This indicates they are more aligned with Shannon entropy-driven weightings, likely benefiting from continuous or numeric criteria (e.g., distance to hospital, number of rooms). As more weight is shifted to binary criteria (Wen), their suitability drops.

Even when rankings (from previous analysis) may remain relatively stable, this plot highlights the actual performance gap. Two alternatives might swap places slightly in ranking but have significantly different RC values. For example, A5 and A2 are close in rank, but A2 has consistently higher RC values, suggesting a more reliable shelter choice.

The slope of each line represents how sensitive an alternative is to changes in φ. Steeper lines (e.g., A1, A7, A10) indicate higher sensitivity, meaning the decision changes drastically depending on the entropy model. Flatter lines (e.g., A3, A12, A5) suggest more robustness and reliability, as their RC scores remain consistently high with little variation.

4.5 Practical discussion

This sensitivity analysis emphasizes the importance of balancing hard infrastructure indicators with qualitative service-based criteria in emergency shelter planning. Policymakers who rely solely on quantitative data may overlook critical but non-numerical features such as accessibility, pet accommodation, and support for different age groups. Conversely, models weighted too heavily toward binary criteria may prioritize options that lack sufficient capacity or safety. The φ-based analysis allows for flexible adaptation to different emergency scenarios and helps identify alternatives that remain resilient under uncertainty.

In order to enhance the interpretability and practical relevance of the hybrid entropy-TOPSIS model, a scenario-based sensitivity analysis was conducted. This approach links different values of the φ parameter to specific emergency response scenarios, reflecting the kinds of criteria that become more or less critical under various real-world conditions. The φ parameter governs the balance between two entropy-based weighting schemes: Shannon entropy, which emphasizes continuous or quantitatively varying criteria, and Wen entropy, which is tailored to binary or crisp decision features. By associating specific φ ranges with disaster contexts, the model's outputs become more policy-relevant and aligned with actual emergency planning needs.

The following scenarios were selected as representative use cases based on regional hazards, demographic concerns, and infrastructure constraints:

4.5.1 Senior Population Evacuation

This scenario models situations where the evacuees are primarily elderly individuals. In such cases, binary or crisp attributes become critically important, such as the availability of elevators, accessibility for wheelchairs, proximity to healthcare facilities, and on-site medical space. These features are typically encoded in binary (yes/no) form and receive greater emphasis when Wen entropy is weighted more heavily. This corresponds to φ values between 0.7 and 1. In this range, the model prioritizes shelter alternatives that are well-equipped to serve vulnerable populations, and alternatives such as A12, A3, and A17 consistently demonstrate high RC scores, indicating their robustness under such conditions.

4.5.2 Winter Emergency Evacuation

This scenario is focused on severe weather conditions common in Manitoba, where factors such as emergency power supply, structural resilience, heating capabilities, and proximity to medical services are essential. These features are typically represented by continuous or ordinal measures. Consequently, φ values from 0 to 0.3 are more relevant, as the model emphasizes Shannon entropy-based weighting. In this range, shelters like A2, A5, and A6 exhibit superior performance due to their larger capacity, structural modernity, and logistical preparedness, making them ideal choices for winter evacuation plans.

4.5.3 Logistical Constraints and Resource-Limited Scenarios

In cases where road access is limited or supply chains are disrupted, the most important criteria include proximity to main roads, food storage capabilities, parking availability, and on-site kitchens or dining facilities. These criteria are a mix of binary and continuous types, suggesting a balanced weighting approach. Therefore, φ values between 0.4 and 0.6 provide the most appropriate modeling condition. In this mid-range, alternatives such as A3, A5, and A10 emerge as stable and high-performing options, with infrastructure and service versatility that make them particularly useful when rapid deployment and self-sufficiency are required. The figure below visually maps these scenarios to the corresponding φ ranges, supporting the contextualization of the sensitivity analysis:

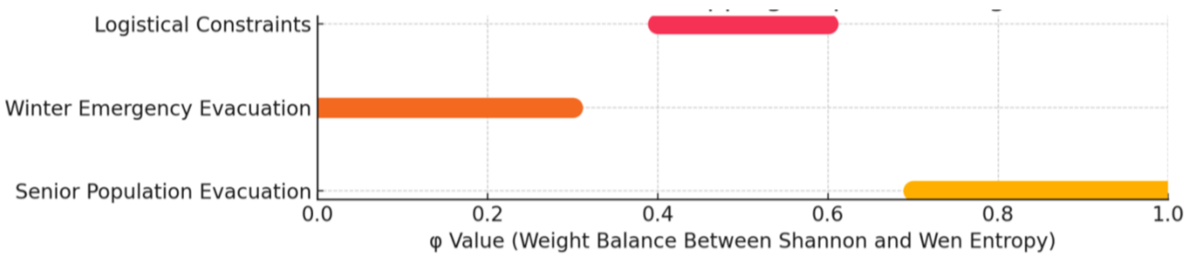

Figure 10: Senario-based mapping to φ Values

Chapter 5

Conclusion

This study presented a decision support framework for evaluating and ranking emergency shelter alternatives using a hybrid entropy-TOPSIS method. The core objective was to address the complexity of shelter selection in disaster contexts by developing a model that integrates both continuous and binary decision criteria in a mathematically rigorous yet practically meaningful way. The model was applied to a real-world case study of hotels in Winnipeg, Manitoba, treating them as potential medium-term emergency shelters in the event of a natural hazard.

To capture the varying importance of shelter features, ranging from quantitative elements like room capacity and proximity to hospitals, to binary factors such as accessibility and the availability of emergency power, a hybrid weighting approach was employed. Specifically, the model combined Shannon entropy and Wen entropy using a parameterized φ value, which allowed a flexible balance between the two methods. This blending mechanism enabled the model to reflect different strategic priorities depending on the nature of the emergency.

One of the main strengths of the model lies in its ability to adapt to diverse real-world scenarios. By conducting a detailed sensitivity analysis across a range of φ values, the model provided insight into which shelters consistently performed well, and which were more sensitive to the type of criteria emphasized. For instance, certain hotels proved to be universally strong candidates across all weight combinations, while others showed situational advantages under specific disaster profiles. This level of insight goes beyond static ranking and offers a dynamic decision-making tool that reflects the evolving priorities in emergency planning.

Importantly, the model's flexibility translates into tangible decision support for policymakers and emergency managers. It can be used not only to pre-select shelters in preparedness phases but also to make informed adjustments during an active emergency response. For example, if the dominant concern in a given situation is elderly evacuees, the model can prioritize shelters with strong accessibility and healthcare features. In contrast, if the situation involves supply chain interruptions or transportation challenges, the model shifts focus to logistics-related attributes.

Overall, the hybrid entropy-TOPSIS framework developed in this study serves as a scalable and adaptable methodology for shelter selection. It bridges the gap between abstract multi-criteria decision-making models and the practical demands of disaster management. By providing a tool that is both analytically sound and context-sensitive, this work contributes to more resilient and responsive emergency planning systems.

The results of this research offer a valuable contribution to the field of disaster response planning by transforming complex, multi-criteria data into actionable insights. For emergency managers, the model serves not merely as a theoretical exercise but as a practical decision-support tool that can guide the selection of shelter facilities based on specific needs, constraints, and populations at risk. Its flexibility allows planners to simulate different emergency conditions and adjust the prioritization of shelters accordingly. This empowers decision-makers to move beyond intuition or single-factor considerations and instead rely on a systematic, evidence-based process. By identifying both universally strong shelter options and conditionally optimal ones, the model supports contingency planning and increases preparedness under uncertainty, ultimately enhancing the resilience and responsiveness of emergency management systems.

Based on the results of the hybrid entropy-TOPSIS model and the detailed sensitivity analysis across varying φ values, several hotels emerged as consistently strong candidates for emergency shelter use. These shelters demonstrated high RC scores and stable rankings regardless of how the model weighted quantitative versus binary criteria, making them the most reliable options for emergency planners.

The Victoria Inn Hotel and Convention Centre Winnipeg (A3) stands out as the most universally optimal shelter. It ranked first across all φ values and showed the highest and most stable RC scores, indicating a strong performance in both structural and service-based criteria. This hotel offers a balanced profile that makes it suitable for nearly any emergency scenario, whether the situation demands capacity, accessibility, or specialized amenities.

Another key offer is the Canad Inns Destination Centre Polo Park (A12), which consistently held the second rank and demonstrated a steadily increasing RC score as φ increased. This pattern indicates that A12 excels particularly in binary or crisp criteria such as pet-friendliness, age-specific services, accessibility features, and support facilities, making it especially well-suited for scenarios involving vulnerable populations such as seniors or families with children.

The Holiday Inn Winnipeg-Airport West (A2) also performs very strongly, ranking in the top three throughout the analysis. It maintains high RC values, particularly under lower φ values where quantitative indicators are emphasized. This suggests it is a solid choice for winter evacuations or disaster situations requiring a strong structural foundation and medical accessibility.

Additional stable performers include the Lakeview Signature (A5) and the Clarion Hotel & Suites (A11). Both hotels maintain top-tier RC scores and low variability in rank across all weighting strategies, which means they offer a reliable combination of physical infrastructure, emergency support capacity, and guest services. These hotels are "safe bets" that remain effective regardless of the changing priorities in emergency response planning.

Other alternatives demonstrate conditional strength. The Sandman Hotel & Suites Winnipeg Airport (A17) improves its performance significantly as φ increases, which makes it particularly well-suited for scenarios where binary criteria, like emergency readiness, food services, and on-site medical support, are prioritized. Similarly, The Grand Winnipeg Airport Hotel by Lakeview (A16) shows a dramatic rise in RC scores under high φ values, making it an excellent shelter choice when evacuation involves seniors or individuals with special accessibility needs.

These results together form a strong foundation for practical, scenario-sensitive emergency planning. By identifying shelters that are not only high-performing but also context-responsive, the model supports a more adaptive and resilient decision-making process.

By equipping EMO with a transparent and repeatable evaluation tool, this model strengthens their ability to make rapid, well-informed decisions under crisis conditions. It supports Manitoba's broader goals in risk reduction, efficient resource deployment, and minimizing the need for disruptive secondary relocations. The adaptability of the model ensures that it can be recalibrated for different scenarios, hazard types, or regions within the province, enhancing the resilience and responsiveness of shelter management systems.

Beyond its immediate application, the model contributes to the development of scalable tools in emergency logistics. Its methodological foundation allows for future enhancements, including the incorporation of GIS and transportation network data to assess travel time, road accessibility, and dynamic hazard impacts such as flooding or blocked routes. Furthermore, expanding the framework to include social equity dimensions, such as prioritizing vulnerable populations, would improve its inclusivity and fairness.

Future research may also consider integrating this hybrid entropy-TOPSIS approach with other multi-criteria decision-making tools, such as the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) or AHP, to enable comparative studies and enhance robustness under uncertainty. Testing the model across different provinces or international settings could further validate its generalizability and contribute to the global discourse on disaster response planning.

Contributions

This thesis advances the field of emergency shelter selection through several significant methodological and practical contributions. Addressing persistent gaps in the literature, the research introduces a novel hybrid entropy-TOPSIS framework that improves the objectivity, adaptability, and operational relevance of MCDM for disaster preparedness.

The study contributes a methodological innovation by combining Shannon entropy and Wen entropy for the calculation of criteria weights. While prior research has typically relied on either subjective technique such as AHP or objective methods like Shannon or CRITIC entropy in isolation, this study is among the first to systematically integrate multiple entropy-based approaches. Shannon entropy captures variability in the data, while Wen entropy refines these weights based on the structural importance of binary criteria. This dual approach enhances both granularity and fairness in weighting, thereby addressing known weaknesses in conventional TOPSIS applications that often underrepresent the decision impact of categorical attributes.

The model is grounded in real-world, operational infrastructure. Unlike much of the existing literature that evaluates hypothetical or vacant land scenarios, this research applies the model to a set of actual hotels in Manitoba, Canada. These facilities are not theoretical constructs but are buildings that could be activated as shelters in real disaster scenarios. The evaluation includes a diverse set of criteria, such as proximity to hospitals, structural resilience, accessibility for vulnerable populations, and service availability, making the results directly relevant to emergency planning agencies. This practical application bridges the gap between academic modeling and deployable emergency solutions.

The research strengthens the policy alignment and institutional validity of shelter selection models by collaborating with the Emergency Management Organization (EMO) of Manitoba. The selection and definition of decision criteria were informed through expert consultation, ensuring that the model reflects the operational realities, legal requirements, and policy guidelines of local emergency response. This collaboration enhances the likelihood of uptake by emergency authorities and demonstrates how academic research can inform real-world decision-making processes.

The thesis addresses a geographic and contextual gap in the literature by focusing on the Canadian urban landscape. Most prior studies in shelter selection have centered on contexts in Asia, the Middle East, or Europe, often neglecting the unique climatic, infrastructural, and demographic challenges present in Canada. By modeling shelter needs in Winnipeg and incorporating rural-urban transition dynamics, transportation constraints, and accessibility concerns, this study introduces a framework tailored to Canadian conditions but generalizable to similar global contexts.

Finally, the model enhances adaptability and scenario-responsiveness through the introduction of a φ parameter, which allows emergency planners to shift weight emphasis between continuous and binary criteria based on the evolving characteristics of a disaster. The associated sensitivity analysis and scenario mapping further provide users with clarity on how rankings change under different operational assumptions. This capability transforms the model into a robust decision-support tool, not only useful for preparedness planning but also flexible enough for use in real-time disaster response.

Together, these contributions address critical methodological, practical, and contextual shortcomings in the current body of shelter selection literature. The result is a comprehensive, empirically grounded, and stakeholder-informed framework that offers both analytical rigor and policy applicability, a valuable asset for researchers and practitioners working to enhance community resilience in the face of disaster.

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