Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

INFLUENCE OF NORMS IN ALLIANCE CHARACTERISTICS OF HUMANITARIAN FOOD AGENCIES: CAPABILITY, COMPATIBILITY AND SATISFACTION

Naimur Rahman Chowdhury[1], Rashik Intisar Siddiquee[1], and Julie Simmons Ivy[2]

[1]Dept. of Industrial and Systems Eng., North Carolina State University, Raleigh, USA
[2]Dept. of Industrial and Operations Eng., University of Michigan, Ann Arbor, USA

ABSTRACT

Hunger relief networks consist of agencies that work as independent partners within a food bank network. For these networks to effectively and efficiently reduce food insecurity, strategic alliances between agencies are crucial. Agency preference for forming alliances with other agencies can impact network structure and network satisfaction. In this paper, we explore the compatibility and satisfaction achieved by alliances between different agencies. We introduce two agency norms: conservative and diversifying. We develop an agent-based simulation model to investigate alliance formation in a network. We evaluate network satisfaction, satisfaction among different types of agencies, and alliance heterogeneity. We test the statistical significance of satisfaction within a norm and between norms for different agencies. Findings reveal that the 'diversifying' norm in the network reduces gaps in satisfaction between strong and weak agencies, ensuring fairness for weaker agencies in the network, whereas the 'conservative' norm favors moderate agencies in the network.

1 INTRODUCTION

In the United States (US), the food insecure population reached 13.6% in 2023, and food banks serve as an intervention to this problem (Park et al. 2024). One in six people in the US are served by food banks and their associated partner agencies, such as food pantries, soup kitchens, and shelter homes (Feeding America 2022). Within a food bank network, these agencies are autonomous and operate to maximize local donation distribution (Reusken et al. 2023). Alliance between agencies is important for creating a strong, resilient network. Such a network would enable agencies to help each other share resources and expertise (Hasnain et al. 2023). This is particularly critical under disaster conditions. Hasnain et al. (2023) explored a food bank network's resilience in the aftermath of Hurricane Florence. Their study finds that agencies wish for a continued cooperation structure that would go beyond the disaster relief scenario. In the humanitarian logistics context, Shaheen and Azadegan (2020) defined collaborative relationships as relationships in which two parties agree to share resources, e.g., knowledge, expertise, personnel, and equipment, to accomplish a commonly shared objective. However, whether agencies form alliances between them depends on their compatibility (Shaheen and Azadegan 2020). Although humanitarian in nature, two entities in a humanitarian network with similar capabilities might compete for resources as they both try to maximize their local allocation (Prendergast 2022). On the other hand, they might collaborate with each other if the mutual benefit or common goal of collaboration outweighs the perceived threat (Sarkar et al. 2001). These relationships lead to creating a social network symbiosis of agencies, where local rules result in a large network-level behavior (Schelling 1971). These local rules are defined as norms, and these norms dictate how the agencies, in this case, try to form alliances with each other. One common norm in such a network is conservative in nature and predominantly influenced by relationship capital, which allows entities with similar capabilities to share operational resources to strengthen collaboration (Sarkar et al. 2001). On the other hand, a norm, diversifying in nature, influences the alliance of agencies with opposite capabilities to reduce potential conflict. In both cases, structural, cognitive, and relational capital concepts play a major role in alliances among the network entities (Najjar et al. 2019).

Specific to humanitarian relief, familiarity with operating capabilities helps identify how compatible and complementary the party's operational standards, procedures, and techniques are. In this paper, we explore the formation of alliances among agencies and the satisfaction achieved in the network, which are influenced by different norms. We focus on exploring the overall satisfaction of different types of agencies in a connected network of resource sharing. First, we develop a set of definitions, including capability, compatibility, and satisfaction in the context of humanitarian logistics. Then, we develop functions for compatibility with respect to different norms followed by a network. Finally, we develop an ABM approach that optimizes the overall satisfaction of the network through alliance formation and network development. We utilize the ABM for different norms to explore how different the connected components are in terms of their ability to follow a particular norm. Furthermore, we explain the obtained results using Kolmogorov-Smirnov (KS) statistical tests. To our knowledge, no previous study has explored the nature of norms in creating alliances in a food bank agency network.

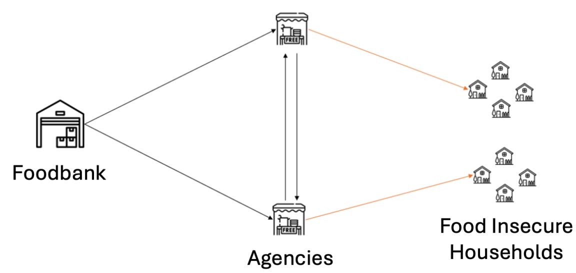


Figure 1: Food bank operations.

2 PROBLEM DESCRIPTION

2.1 Agencies in Food Bank Networks

An outline of the food bank operation is provided in Figure 1. The food bank network is composed of food banks, their branches, and agencies in the first two echelons, respectively. The food-insecure households are the final echelon. These agencies are independent and autonomous organizations that receive donations and other support from the food bank. However, these agencies can collaborate with one another based on their capability and compatibility to form alliances with others.

2.2 Network Properties

In this section, we define different properties of agencies that affect the symbiosis in the agency network.

2.2.1 Capability

Agency capability defines the combined resource level in human capital, information technology, and operational scale of the agency (Marchiori et al. 2022). In other words, the availability of volunteers for operations, the agency's technological resources to manage donation inventory, distribution, volunteer assignments, and operational ability, such as storage capacity, refrigeration capacity, and number of people served, collectively define the capability of an agency. We define the capability of an agency in Equation (1).

$$\xi_i = f(x^i_{OC}, x^i_{TC}, x^i_{SC}) \tag{1}$$

Here, $\xi_i \in [0,1]$ is the scaled capability score of an agency i which is a function of organizational, (x^i_{OC}), technological (x^i_{TC}) and social (x^i_{SC}) capital. Social capital is an agency's ability to collaborate and work with partners and volunteers. Technological capital is the resource capability of an agency in terms of technological infrastructure and innovation. Finally, organizational capital defines an agency's ability to manage resources and operations. ξ_i taking a score 0 suggests that the agency i has the least capability, whereas, ξ_i taking the value 1 suggests that agency i has the highest capability in the network. We assume $\xi_i \sim \mathscr{N}(\mu, \sigma)$ follows a normal distribution and categorizes agencies into three classes, i.e., strong, moderate, and weak agencies in the network. There have been several attempts to explore the inter-capital functional relationships and the relationship between capital, supply chain integration, information sharing, and collaboration. Ataseven et al. (2018) conducted a survey-based investigation on food banks where they explored the relationship between intellectual capital and supply chain integration; Intellectual capital was an amalgamation of three constructs: Human Capital, Organizational Capital, and Social Capital. Lee and Ha (2018) took a similar approach to illustrate the connection with information sharing and capital. However, the current study's major focus is to utilize the agency's relative capabilities to define the norms of cooperation. Rather than defining a complete functional form of capital and the capability score, the authors focused on the scope of our simulation framework, where the relative ordering of agencies (not the absolute capability values) drives the compatibility and satisfaction calculations. Assuming a normal assumption here is reasonable, as the capability of an agency is the sum of its capital across three aspects, which tends to follow the central limit theorem.

2.2.2 Compatibility

Compatibility is an agency's tendency to create an alliance with another agency based on its own capability, which is dependent on the norms a particular agency network follows. In partnership, characteristics, resources, and cultural and operational compatibilities determine the alliance performance between two entities (Sarkar et al. 2001). On the other hand, from a social network perspective, entities prefer to connect with homogeneous or similar types of entities for satisfaction (Abella et al. 2022). We consider both perspectives and define two norms followed by agencies in a network, as described in the following section. Here, we opt for predefined behavioral rules as norms, as they represent patterns of interaction that may have emerged or been reinforced over time and the history of collaboration. Similar patterns of norm emergence are discussed in the literature where the society converges towards a convention when agents perform the same action (Andrighetto et al. 2013). Similar norm emergence has been discussed in a life cycle context in other studies by Savarimuthu and Cranefield (2011) and Hollander and Wu (2011).

- **Norm1- Conservative**: Under the conservative norm, an agency's compatibility to make alliances with other agencies is influenced by operational similarity. In other words, agencies with similar capabilities have higher compatibility scores because of the mutual resource level that increases their complementarity (Sarkar et al. 2001). To define the conservative norm, we use a scaled inverse Sigmoid function in Equation (2).

$$T_{ij} = \sigma(\xi_i, \xi_j) = \frac{1}{1 + e^{k(|\xi_i - \xi_j| - 0.5)}} \tag{2}$$

Here, $|\xi_i - \xi_j|$ represents the dissimilarity in capability, i.e., the absolute difference between the capability of agencies i and j. T_{ij} is the compatibility score of agency i to make alliance with agency j. Under Norm1, when the two agencies have similar capability ($|\xi_i - \xi_j|$ is near 0), they have a high T_{ij} score. k is the scale factor to make the T_{ij} scores in range [0,1].

- **Norm2- Diversifying**: To consider intrinsic competitive tendency between entities in a network, we consider diversifying norms. Here, agencies with the same capability are competitors and do not want to collaborate with each other. In other words, agencies with dissimilar capabilities have higher compatibility scores to reduce conflict of interest (Sarkar et al. 2001). We use a scaled Sigmoid function in Equation (3).

$$T_{ij} = \sigma(\xi_i, \xi_j) = \frac{1}{1+e^{-k(|\xi_i-\xi_j|-0.5)}} \tag{3}$$

Here, T_{ij} is high when the dissimilarity is high. We plot values for both norms in Figure 2 to visualize how compatibility scores vary with different dissimilarities between agencies. Note, a shift of 0.5 in both Equations 2 and 3 was introduced to scale the Sigmoid function to map the dissimilarity value domain [0,1]. For Norm2, when the dissimilarity is 0, the function provides the lowest compatibility score (0), whereas when the dissimilarity approaches 1, the function provides the highest compatibility score (1). As we want the compatibility to be somewhere between the extremes when dissimilarity is also moderate (0.5), we consider the 0.5 shift to be a good choice. Additionally, the parameter k in the equations determines the sharpness of the transition of the compatibility with dissimilarity values. In our model, we want agency symbiosis to have a gradual change in compatibility with the change in dissimilarity, and a sharp drop when the dissimilarity gap increases. This puts more importance on an alliance with a closer choice for Norm1 and the opposite for Norm2. This can be achieved with a large k parameter. We initialize with $k = 10$ for sharp transitions and later study the effect of a change in the parameter on the overall network dynamics.

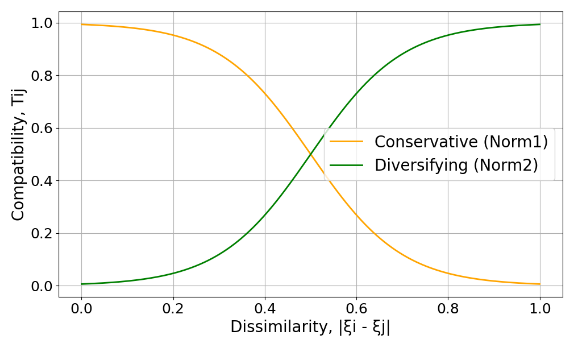


Figure 2: Compatibility scores for different norms.

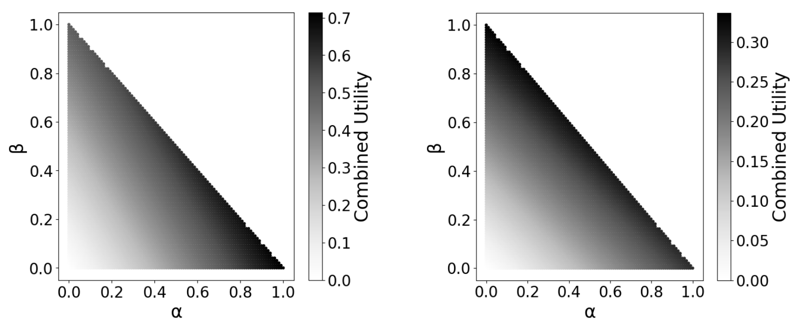
2.2.3 Satisfaction

Satisfaction is the core of an alliance in a network, and it determines how much benefit or gain an agency receives while making an alliance with another agency. In this study, satisfaction is defined as a function of two main components of agencies, i.e., compatibility and proximity. The satisfaction ϕ_{ij} of agency i while making an alliance with agency j is defined in Equation (6).

$$\phi_{ij} = (\alpha \times T_{ij} + \beta \times \pi_{ij})e^{-\lambda Dij}, \forall i, j \neq i \tag{4}$$

Here, π_{ij} is the norm reward, which is $\frac{|\xi_i+\xi_j|}{2}$ for Norm1 and $|\xi_i - \xi_j|$ for Norm2 in the same scale of [0,1]. We chose this norm reward to represent the intrinsic preference alignment for two agencies. Whereas the compatibility reward T_{ij} is more representative of inter-agency credibility, π_{ij} can supplement it by incorporating ideological alignment directly in the objective. We add those two objectives to get the utility $(\alpha \times T_{ij} + \beta \times \pi_{ij})$ for agency collaboration, where α and β are weight factors for the compatibility and reward terms. The reason to choose addition instead of multiplication of these terms is to address the linear trade-off, which is more convenient to interpret in alignment with multiple-attribute utility theory models (Winterfeldt et al. 1975). For different combinations of α and β values, we observe total utility. As shown in Figure 3, Norm1 tends to put higher weight on α for greater utility, whereas Norm2 maximizes utility in both extremes. Therefore, we heuristically choose $\alpha = 0.8$, $\beta = 0.2$, as increasing weights on

α tends to increase the total utility of agency alliance for both. D_{ij} defines the proximity between two agencies. Satisfaction decreases exponentially when the distance between two agencies increases to capture the proximity of practical resource-sharing with a decay rate of λ, which can affect the overall satisfaction of agency collaboration. We set the decay rate $\lambda = 1$ to allow D_{ij} to directly affect the satisfaction value.



(a) Total utility for Norm1. (b) Total utility for Norm2.

Figure 3: Total utility for different norms.

3 SIMULATION MODEL

The objective of the simulation model is to find the network structure of agencies that maximizes overall satisfaction at the network level and at the agency level. This is achieved by developing an ABM with agents being the agencies in the network. In the simulation model, agencies form new and dissolve older alliances depending on the improvement in the aggregated satisfaction of agencies in the current network. First, for the agencies, we define agent properties in Table 1. To develop the simulation environment, we consider the following assumptions for our model.

Table 1: Agent properties in simulation.

Name	**Description**
Type	Strong, Moderate or Weak. Follows ξ_i described in Section 2.2.1
Location	Coordinate (x,y) of the location of an agency in the network
Distance (D_{ij})	Euclidian distance of agency i from agency j, $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
Compatibility (T_{ij})	Compatibility score of agency i with agency j described in Section 2.2.2
Satisfaction (ϕ_i)	Aggregated satisfaction of agency i, with all j in its alliance, $\phi_i = \sum_{j \in \mathscr{C}_i} \phi_{ij}$

Model Assumptions:

- One type of norm for compatibility is followed by all agencies within a network. This assumption is considered to model networks for different norms to highlight how satisfaction is impacted when the network follows one norm as opposed to the other.
- Capability of agencies follows a normal distribution $\xi_i \sim \mathscr{N}(\mu, \sigma)$ and categorizes agencies into three classes, i.e., strong, moderate, and weak agencies. The classification occurs in the $[\mu - \sigma, \mu + \sigma]$ boundary. The weak, moderate, and strong agencies have ξ_i scores in the range [0,0.35), [0.35,65], (.65, 1], respectively.
- Agencies do not consider an alliance with another agency if the distance, D_{ij}, is not within a threshold D. In practical settings, to maintain collaboration for physical resource sharing, agencies may have to be in close proximity to each other. Therefore, we set $D = 10mi$ as a reasonable

threshold for agency collaboration. We define $\mathscr{F} \in \{j \in \mathscr{A} \setminus \mathscr{C}_i \mid D_{ij} \leq D,\ j \neq i\}$ as the set of candidate agencies that are not in the current alliance network ($\mathscr{C}_i$) of agency i. Here, $\mathscr{A}$ is the set of all agencies.

- The number of alliances an agency can make has a threshold limit $\mathscr{L}$. We assume this to reduce redundancy and overcrowding in collaboration.

Algorithm 1 Agent alliance formation

$\phi_{\text{i-old}} \leftarrow \sum_{j \in \mathscr{C}_i} \phi_{ij}$
$\mathscr{F} \leftarrow \{j \in \mathscr{A} \setminus \mathscr{C}_i \mid D_{ij} \leq D,\ j \neq i\}$
Random shuffle $\mathscr{F}$
for $j \in \mathscr{F}$ **do**
    $T_{ij} \leftarrow \sigma(\xi_i, \xi_j)$
    $\phi_{ij} \leftarrow (\alpha \times T_{ij} + \beta \times \pi_{ij}) e^{-Dij}$
    if $\phi_{ij} > 0$ **then**
        $\mathscr{C}_i \leftarrow \mathscr{C}_i \cup \{j\}$; $\mathscr{C}_j \leftarrow \mathscr{C}_j \cup \{i\}$
        $\phi_{\text{i-new}} \leftarrow \sum_{k \in \mathscr{C}_i} \phi_{ik}$
        if $\phi_{\text{i-new}} > \mathscr{M} \cdot \phi_{\text{i-old}}$ **then**
            while $|\mathscr{C}_i| > \mathscr{L}$ **do**
                Remove $k^* = \arg\min_{k \in \mathscr{C}_i} \phi_{ik}$ from $\mathscr{C}_i$
            end while
        else
            $\mathscr{C}_i \leftarrow \mathscr{C}_i \setminus \{j\}$; $\mathscr{C}_j \leftarrow \mathscr{C}_j \setminus \{i\}$
        end if
    end if
end for

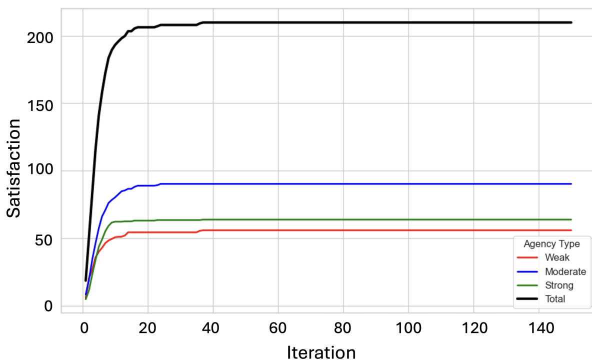
Algorithm 2 Network step

for $i \in \mathscr{A}$ **do**
    Execute Algorithm 1
end for
$\phi_i \leftarrow \sum_{i \in \mathscr{A}} \sum_{j \in \mathscr{C}_i} \phi_{ij}$

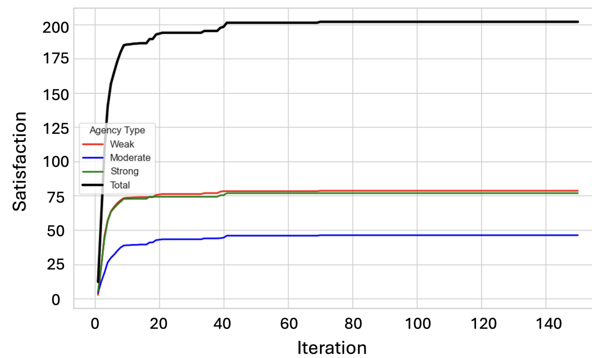
The formation of alliances for each agency i follows Algorithm 1. First, for each agency, the set of candidate partners ($\mathscr{F}$) are chosen. Then, the algorithm calculates ϕ_{ij} for each new potential connection. We ensure that the new ϕ_{i-new} is reasonably higher by a factor of $\mathscr{M}$ than the previous one for choosing the best alliances. We choose $\mathscr{M} = 1.05$, implying that at least a 5% improvement over the previous connection allows exploring a new connection in the model. In each iteration, the model makes the best alliance and removes the worst alliance if the number of connections exceeds the threshold $\mathscr{L}$. We set a threshold of $\mathscr{L} = 10\%$ of the total agencies in the network, which is reasonable for a large network of agencies. Note that $\mathscr{L}$ does not restrict an agency from being in an alliance group (cluster) that is bigger than $\mathscr{L}$. In other words, even if an agency can make at most $\mathscr{L}$ alliances, it can still be in a cluster that has more than $\mathscr{L}$ agencies with indirect connections. We apply the same alliance algorithm to the entire network, as shown in Algorithm 2.

4 RESULTS AND DISCUSSIONS

To run the simulation, we use MESA: Agent-based modeling in Python (Hoeven et al. 2025). Using agent schedulers in MESA, we update the alliances of each agency in each step of the system-level simulation. We use simulated data for agency properties of 150 agents and keep the seed consistent among different simulations within a fixed norm and between different norms. This ensures that the results between different norms are consistent and comparable. For each simulation run, for each type of norm, we get the overall satisfaction and satisfaction by agency type, converging after a number of iterations. Figures 4a and 4b show the satisfaction score for the two norms, respectively. From visual inspection, it is evident that there is a difference in how different types of agencies achieve overall satisfaction in the conservative (Norm1) and diversifying (Norm2) norms. Table 2 presents a summary of the results from 100 simulation replications, which shows Norm1 has 16.45% higher total satisfaction than Norm2. Whereas moderate agencies on average dominate in Norm1, for the other two types, Norm2 results in a higher satisfaction value.



(a) Satisfaction in conservative norm.



(b) Satisfaction in diversifying norm.

Figure 4: Satisfaction score in agency network.

Table 2: Mean and standard deviation of satisfaction.

Metric	***Norm1* mean**	***Norm1* std**	***Norm2* mean**	***Norm2* std**
Total	244.94	19.02	210.33	20.67
Strong	1.54	0.20	1.77	0.21
Moderate	1.86	0.17	0.88	0.10
Weak	1.42	0.16	1.72	0.22

For inference, we construct three different hypotheses and investigate the results based on them. The hypotheses are as follows.

Ha_0: No significant difference between overall satisfaction achieved for different norms.

Hb_0: No significant difference between satisfaction achieved for different types of agencies (strong, moderate, and weak) for different norms.

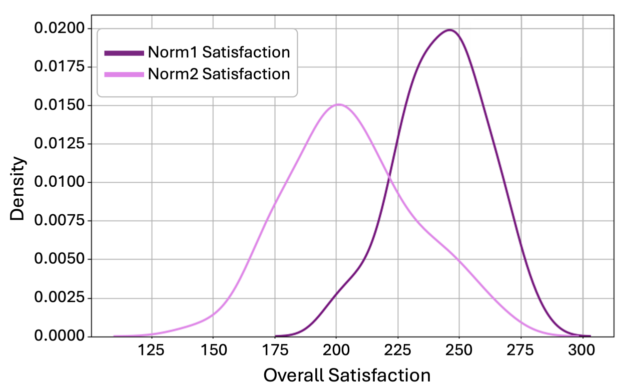
Hc_0: No significant difference between satisfaction achieved in different types of agencies within a norm.

To investigate Ha_0 and Hb_0, we run multiple simulations for both norms and use kernel density estimation (KDE) to visualize the distribution of overall satisfaction and average satisfaction of strong, moderate, and weak agencies for both norms. Figure 5 presents the density functions for two norms. We also present the KS test statistics in Table 3. From Figure 5a and Table 3, we observe that the overall satisfaction achieved for both norms is statistically different, while Norm1 achieves a higher mean value. From Figure 5a - 5d, it is also clear that moderate agencies differ significantly in two different norms while pushing the overall satisfaction in Norm1. For the other two categories (strong and higher), we see that the average satisfaction is higher in Norm2. So, we reject both Ha_0 and Hb_0. We also observe in Figure 4a and 4b that moderate agencies were the influential factor for pushing overall satisfaction values in Norm1. In contrast, Norm2 reduces the gap between weak and strong agencies. To look at this closely, we also analyze the satisfaction of different agencies within a norm. To understand this, we plot the distribution of satisfaction scores for different agencies for a single simulation run in Figure 6. Moreover, we run multiple simulations to test Hc_0 for within-norm satisfaction and present the KS-statistic in Table 4. Results highlight our previous visual analysis in Figure 6 that Norm2 minimizes the gap between the satisfaction score for strong and weak agencies, giving weak agencies more fairness in the network.

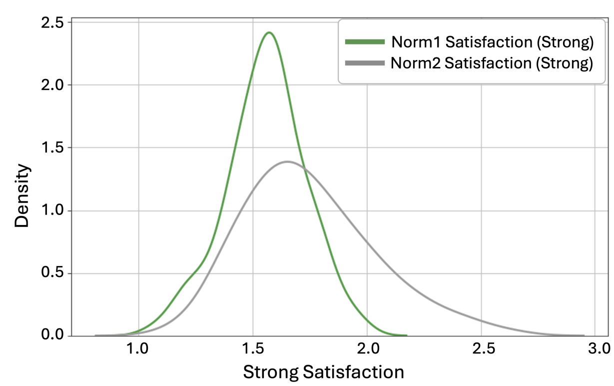
Furthermore, at the convergence of the simulation, agencies in the network form clusters of alliances,

Table 3: KS test for between-norm satisfaction.

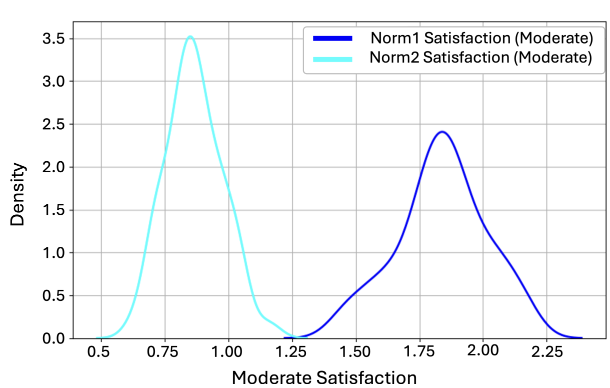
	KS statistic (D)	p-Value (pr > D)
Overall	0.66	0.00
Strong	0.34	0.00
Moderate	1.00	0.00
Weak	0.58	0.00



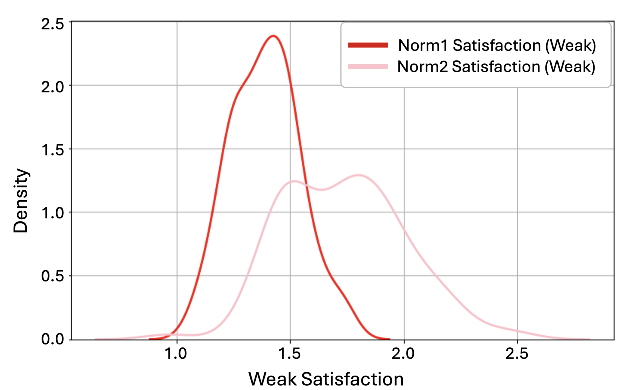
(a) Overall satisfaction for different norms.



(b) Satisfaction in strong agencies.

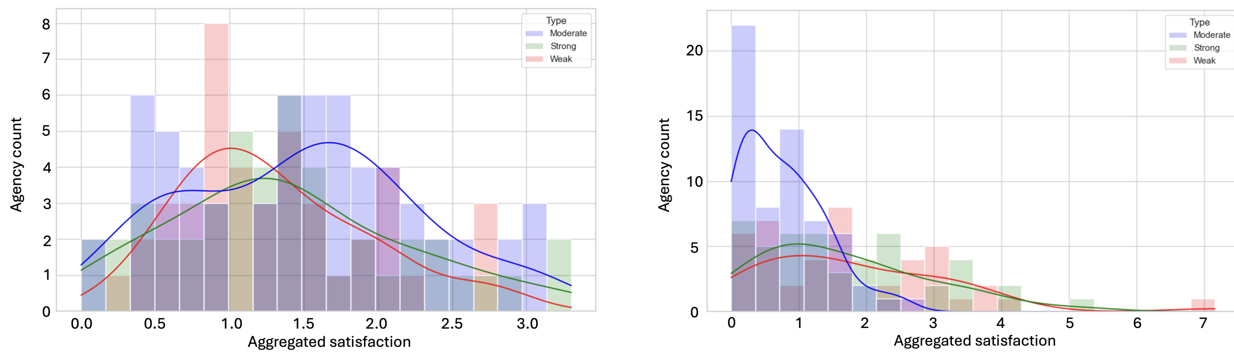


(c) Satisfaction in moderate agencies.



(d) Satisfaction in weak agencies.

Figure 5: KDE for satisfaction scores for different norms.



(a) Conservative norm. (b) Diversifying norm.

Figure 6: Satisfaction score in agencies within a norm.

Table 4: KS test for within-norm satisfaction.

Comparison	**KS statistic (Norm1)**	**p-value (Norm1)**	**KS Statistic (Norm2)**	**p-value (Norm2)**
Weak vs Moderate	0.81	0.00	0.99	0.00
Weak vs Strong	0.48	0.00	0.08	0.91
Moderate vs Strong	0.63	0.00	0.99	0.00

as shown in Figure 7. We want to analyze whether different norms alliance clusters result in different heterogeneity, which is a measure of clusters having different types of agencies, resulting in diverse alliance groups. We define the heterogeneity H of a network in Equation (5).

$$H = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{1}{|\mathscr{A}_k|}\sum_{i\in\mathscr{A}_k}\sum_{j\in\mathscr{C}_i} I_i\right) \tag{5}$$

Here, K is the number of clusters formed in the network, and $\mathscr{A}_k$ is the set members in cluster k. $I_i \in \{1,0\}$ is a binary variable as follows.

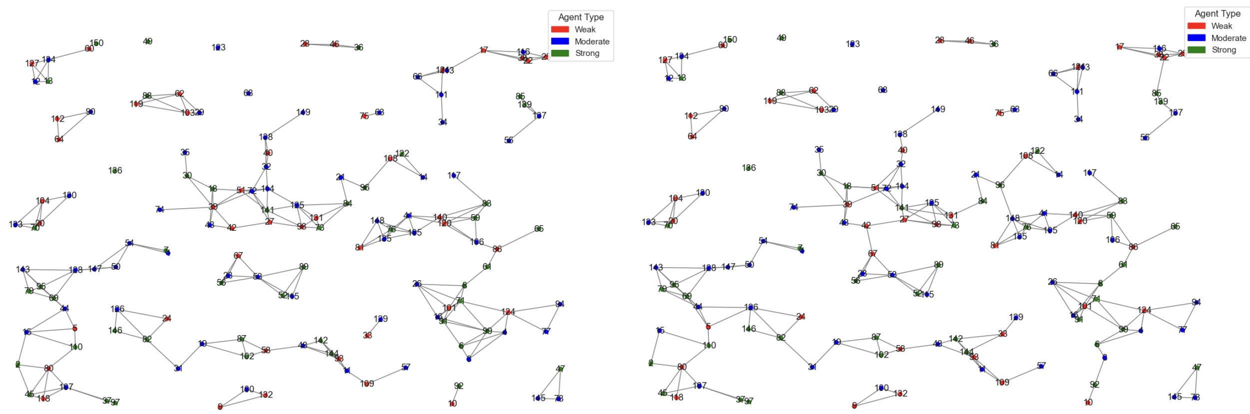
$$I_i = \begin{cases} 1, & \text{if agency } type(i) \neq type(j) \\ 0, & \text{otherwise} \end{cases}$$

To analyze heterogeneity in different norms, we test our final hypothesis, Hd_0: No significant difference between heterogeneity in different norms.

We perform the KS test for H with multiple simulations to plot the KDE in Figure 8 and show the results in Table 5. Although results show that there is no significant difference in heterogeneity obtained between the two norms, from Figure 8, we observe that Norm2 has higher average heterogeneity than Norm1, allowing more diverse agencies to be in agency alliance clusters. This supports our previous claim of Norm2 ensuring fairness for weaker agencies to be in alliance clusters.

Table 5: KS test for heterogeneity.

	KS statistic	**p-value**
Heterogeneity	0.12	0.47



(a) Conservative norm.

(b) Diversifying norm.

Figure 7: Agency network of alliance clusters.

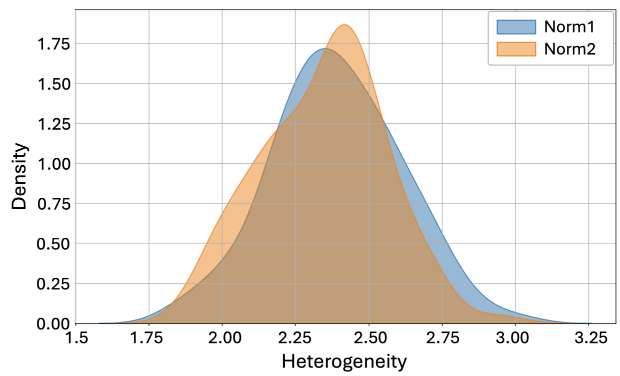


Figure 8: KDE for heterogeneity for different norms.

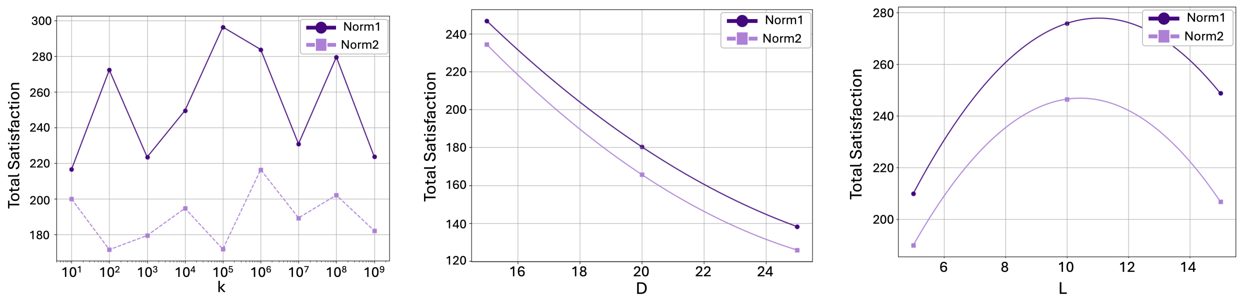
4.1 Sensitivity Analysis

Figure 9 presents the sensitivity analysis for three important model parameters. In Figure 9a, we present the sensitivity for k used for steepness in the compatibility when approaching greater dissimilarity in Equation 2 and 3. We start with a large k of 10 for our model requirement, and increase the k on a logarithmic scale. The satisfaction values for both norms oscillate, creating local maxima. The gap between Norm1 and Norm2 varies, ranging from 72.51% to as low as 8.25%. For D in 9b, we observe a monotonic decrease with increasing threshold value while keeping a similar gap in total satisfaction for the norms. Finally, we observe both norms approaching maximum satisfaction when $\mathscr{L}$ approaches 10, suggesting an optimal average number of connections for each agency in the network.

5 CONCLUSION

In this paper, we analyzed the satisfaction level of different types of agencies following a particular norm. Additionally, we analyzed overall network satisfaction when the network follows different norms. Statistical results show that there is a significant difference in overall satisfaction in the network. However, moderate agencies influence the overall satisfaction with the conservative norm, while weaker agencies have the least satisfaction with this norm.

On the other hand, the diversifying norm increases fairness in the network by reducing the gap between strong and weak agencies, but moderate agencies result in the lowest satisfaction level. The analysis



(a) Sensitivity for k.   (b) Sensitivity for D.   (c) Sensitivity for $\mathscr{L}$.

Figure 9: Sensitivity analysis of model parameters.

suggests that a network should have a balance between these two norms to ensure fairness in satisfaction levels among all types of agencies.

Future work for this paper may include considering a mixture of different proportions of norms followed within a network to analyze the satisfaction level further. The mixture of networks can be categorized by type-specific domination, such as, mixed network dominated by weak agencies. Additionally, this study assumes that the capability scores of agencies are normally distributed and replaces the functional decomposition of the capability score with a simple normal distribution for relative scoring of agencies. This may be extended in future work by using real data to capture different distribution fits for the agencies and analyze the satisfaction for different types of agencies. Different sizes of networks can also be analyzed to see if differences in heterogeneity become significant for different norms.

We acknowledge the distinction of emergent societal norms of collaboration among agencies and predefined behaviors for agencies as defined in this study; we wish to extend this to explore the former in future iterations. Furthermore, we used simulated data with generalized capital values, assuming a normal distribution. The findings from these tests can be further validated in real-world settings. However, acquiring real-world data is challenging given that the agencies are independent organizations with constrained human resources. Despite that, there is scope for creating proxy variables from observable variables. These real data can be utilized along with dynamic norm emergence can be a potential avenue to explore in the future.

ACKNOWLEDGMENTS

This work is supported by the U.S. National Science Foundation Grant numbers 2125600 and 2234598.

REFERENCES

Abella, D., S. M. Maxi, and J. Ramasco. 2022. "Aging Effects in Schelling Segregation Model". *Scientific Reports* 12(1):19376 https://doi.org/10.1038/s41598-022-23224-7.

Andrighetto, G., C. Castelfranchi, E. Mayor, J. McBreen, M. Lopez-Sanchez, and S. Parsons. 2013. "(Social) Norm Dynamics". *Dagstuhl Follow-Ups* 4:135–170 https://doi.org/10.4230/DFU.Vol4.12111.135.

Ataseven, C., A. Nair, and M. Ferguson. 2018. "An Examination of the Relationship between Intellectual Capital and Supply Chain Integration in Humanitarian Aid Organizations: A Survey-based Investigation of Food Banks". *Decision Sciences* 49(5):827–862 https://doi.org/10.1111/deci.12300.

Feeding America 2022. "49M People Seek Hunger Relief". https://www.feedingamerica.org/about-us/press-room/Charitable-Food-Assistance-2022, Accessed 15th February 2025.

Hasnain, T., T. N. Walton, K. Odubela, S. McConnell, L. Davis, J. Ivy, *et al.* 2023. "Resiliency Within the Socio-ecological System of a Large Food Bank Network: Preparing, Mitigating, Responding, and Recovering from Hurricane Florence". *International Journal of Disaster Risk Reduction* 88:103580 https://doi.org/10.1016/j.ijdrr.2023.103580.

Hoeven, E. T., J. Kwakkel, V. Hess, T. Pike, B. Wang, and J. Kazil. 2025. "Mesa 3: Agent-based Modeling with Python in 2025". *Journal of Open Source Software* 10(107):7668 https://doi.org/10.21105/joss.07668.

Hollander, C. D., and A. S. Wu. 2011. "Using the Process of Norm Emergence to Model Consensus Formation". In *2011 IEEE Fifth International Conference on Self-Adaptive and Self-Organizing Systems*, 148–157 https://doi.org/10.1109/SASO.2011.26.

Lee, C. H., and B. C. Ha. 2018. "The Impact of Buyer-supplier Relationships' Social Capital on Bi-directional Information Sharing in the Supply Chain". *Journal of Business & Industrial Marketing* 33(3):325–336 https://doi.org/10.1108/JBIM-01-2017-0021.

Marchiori, D. M., R. G. Rodrigues, S. Popadiuk, and E. W. Mainardes. 2022. "The Relationship between Human Capital, Information Technology Capability, Innovativeness and Organizational Performance: An Integrated Approach". *Technological Forecasting and Social Change* 177:121526 https://doi.org/10.1016/j.techfore.2022.121526.

Najjar, M. S., L. Dahabiyeh, and M. Nawayseh. 2019. "Share If You Care: The Impact of Information Sharing and Information Quality on Humanitarian Supply Chain Performance - a Social Capital Perspective". *Information Development* 35(3):467–481 https://doi.org/10.1177/0266666918755427.

Park, A., J. Chen, and A. Bustamante. 2024. "Adverse Consequences of Food Insecurity among US Adults beyond Health Outcomes". *American journal of preventive medicine* 66(1):146–153 https://doi.org/10.1016/j.amepre.2023.09.003.

Prendergast, C. 2022. "The Allocation of Food to Food Banks". *Journal of Political Economy* 130(8):1993–2017 https://doi.org/10.1086/720332.

Reusken, M., F. Cruijssen, and H. Fleuren. 2023. "A Food Bank Supply Chain Model: Optimizing Investments to Maximize Food Assistance". *International Journal of Production Economics* 261:108886 https://doi.org/10.1016/j.ijpe.2023.108886.

Sarkar, M. B., R. Echambadi, S. T. Cavusgil, and P. S. Aulakh. 2001. "The Influence of Complementarity, Compatibility, and Relationship Capital on Alliance Performance". *Journal of the academy of marketing science* 29:358–373 https://doi.org/10.1177/03079450094216.

Savarimuthu, B. T., and S. Cranefield. 2011. "Norm Creation, Spreading and Emergence: a Survey of Simulation Models of Norms in Multi-agent Systems". *Multiagent and Grid Systems* 7(1):21–54 https://doi.org/10.3233/MGS-2011-0167.

Schelling, T. C. 1971. "Dynamic Models of Segregation". *The Journal of Mathematical Sociology* 1(2):143–186 https://doi.org/10.1080/0022250X.1971.9989794.

Shaheen, I., and A. Azadegan. 2020. "Friends or Colleagues? Communal and Exchange Relationships During stages of Humanitarian Relief". *Production and Operations Management* 29(12):2828–2850 https://doi.org/10.1111/poms.13254.

Winterfeldt, D. V., F. Detlof, and F. W. Fischer. 1975. "Multi-attribute Utility Theory: Models and Assessment Procedures". In *Utility, Probability, and Human Decision Making: Selected Proceedings of an Interdisciplinary Research Conference, Rome, 3–6 September, 1973*, 47–85 https://doi.org/10.1007/978-94-010-1834-0_3.

AUTHOR BIOGRAPHIES

NAIMUR RAHMAN CHOWDHURY is a PhD student and Graduate Research Assistant at Edward P. Fitts Department of Industrial and Systems Engineering at North Carolina State University. His research focuses on humanitarian logistics, notably the hunger-relief supply chain under extreme events. He uses stochastic optimization, integer programming, simulation, and statistical learning methods for solving humanitarian logistics problems. His email address is nchowdh2@ncsu.edu.

RASHIK I. SIDDIQUEE is Ph.D. student at the department of Industrial and Systems Engineering at North Carolina State University. He received his bachelors in mechanical engineering and masters in finance, both from Bangladesh. His research interests revolve around food insecurity, rescue and food bank operations. His e-mail address is rsiddiq2@ncsu.edu.

JULIE SIMMONS IVY is a Professor and Chair of the Department of Industrial and Operations Engineering at the University of Michigan. Dr. Ivy is also the Edgar S. Woolard Professor Emerita of the Edward P. Fitts Department of Industrial and Systems Engineering at North Carolina (NC) State University. She has an extensive background in decision-making under conditions of uncertainty using stochastic and statistical modeling. She joined the University of Michigan College of Engineering faculty after 16 years on the NC State faculty and several years on the faculty of the Ross School of Business at the University of Michigan. Dr. Ivy received her BS and PhD in Industrial and Operations Engineering from the University of Michigan. She also received her MS in Industrial and Systems Engineering from Georgia Tech. Her email address is jsivy@umich.edu and her website is https://jsivy.engin.umich.edu.