

Leveraging place-based social capital to decentralize emergency resource allocation in communities

Olivia Wang^{a,b}, Zhengyang Li^{c,d}, Cynthia Chen^{b,c,*}

^aTsinghua Shenzhen International Graduate School, Tsinghua University, China

^bDepartment of Industrial and Systems Engineering, University of Washington, Seattle, WA 98195, USA

^cDepartment of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195, USA

^dDepartment of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong, P.R. China

Abstract

Utilizing the place-based social capital within communities to enhance the efficiency of disaster response when disasters strike is worth exploring. This study focuses on the ‘last mile’ distribution of emergency supplies during disasters, emphasizing the potential of peer-to-peer sharing driven by social capital for effective distribution. We proposed a quantitative analysis of community social networks and developed a decentralized resource allocation method. The findings indicate that decentralized resource allocation can achieve higher average satisfaction and resource coverage rates compared to the traditional centralized method. Moreover, the applicability of decentralized resource allocation varies, influenced by factors such as residents’ sharing preferences and the number of social ties. One key factor in implementing the decentralized resource allocation scheme is having a subset of residents willing to share with the majority.

Keywords: Decentralized emergency resource allocation, Place-based social capital, Peer-to-peer sharing, Sharing preference, Disaster response

1. Introduction

The world has witnessed an increasing trend in natural disasters in the last several decades ([Ripple et al., 2022](#)). In 2022 alone, the United States experienced 18 billion-dollar disasters ([NCEI, 2023](#)), e.g., Texas Hail Storms and Kentucky and Missouri Flooding. When a disaster happens, the disaster response agencies will gather and transport disaster relief resources to the affected area, wherein the judicious allocation of emergency resources is pivotal for protecting affected residents and facilitating post-disaster recovery ([Hu et al., 2016](#), [Guo et al., 2019](#)). In practice, a common method of emergency resource allocation is *fixed-point distribution*, where relief resources are delivered to one or multiple fixed locations for victims to come and collect, as illustrated in Fig. 1(b). For example, following Hurricane Katrina’s strike on New Orleans in 2005 ([Pipa, 2006](#)), the Federal Emergency Management Agency (FEMA) and the Red Cross established several fixed distribution points in the affected areas to supply food, drinking water, medical equipment, and other essential relief materials. After the 2010 earthquake in Haiti ([Margesson and Taft-Morales, 2010](#)), non-governmental organizations (NGOs) and the United Nations set up regular distribution points in Port-au-Prince and other severely affected cities, providing food, water, and medical supplies to the affected population. To better guide the practice of fixed-point distribution, the National County Logistics Planning ([DEM, 2016](#)) offers guidance for the operation, location, and evaluation of distribution points. The Federal Emergency Management Agency ([FEMA, 2015](#)) also provided guidelines for distributing relief supplies.

Although the fixed-point distribution is widely adopted in practice, it is a top-down, governmental, and centralized emergency resource allocation method, which overlooks the “last-mile”

*Corresponding author.

Email address: qzchen@uw.edu (Cynthia Chen)

delivery of emergency resources. In a disaster environment, a minority of vulnerable residents might struggle to access resources (Dynes, 2006). For instance, the elderly might be unable to obtain resources due to mobility issues, travel barriers, or lack of timely relief information (Fernandez et al., 2002). Further, Klinenberg (2015) found that isolated groups of older people were most likely to die, even undetected, by studying the 1995 Chicago heat event. Amid the chaotic disaster environment, it is usually a great challenge for community managers to clearly understand the disaster and resource status of all families in the community (Gunessee et al., 2018), while community residents themselves know better the status of other community members and informal contacts, especially neighbors, often act as the actual first responders (Scanlon et al., 2014).

Indeed, local or place-based social and civil networks often play an important role in disaster relief and emergency resource allocation (Aldrich, 2014). Empirical evidence suggests that many neighbors check on the well-being of others nearby and provide immediate life-saving assistance (Wasserman and Faust, 1994, Aldrich and Meyer, 2015). During the 1995 Kobe earthquake, most of those rescued were saved by neighbors rather than firefighters (Aldrich, 2011). During the 2000 Walkerton crisis, when trucks carrying relief supplies arrived in Walkerton prior to coordination with the emergency operations center and municipal authorities, community members, including municipal employees, forklift operators, and business owners, effectively coordinated the distribution of resources (Murphy, 2007). Some residents even volunteered to deliver water to those unable to reach the distribution centers. During the freezing period in Texas in February 2021, community residents helped each other through the devastating winter storm (Martinez, 2021). These documents suggest that leveraging place-based social networks may fill important gaps in the “last-mile” delivery of emergency resources during times of disaster.

Noteworthy, the place-based social network is a form of *social capital* (Meyer, 2018). Hanifan (1916) introduced the concept of social capital, defining it as the goodwill, friendships, mutual sympathy, and social interactions between a group of individuals and families constituting a social unit. Morsut et al. (2022) consolidated views from various scholars, defining social capital as norms, values, trust, and networks embedded within society, which can provide resources for mutual support and promote coordination and collaboration in the face of risks and crises. Various studies demonstrate social capital can stimulate a community’s collaborative behavior (Takano and Nomura, 2023), enhance individual resilience (Faas and Jones, 2017), and support more rapid household recovery (Sadri et al., 2018) in disaster scenarios. While the role of social capital in disasters is recognized, most studies remain qualitative, and the potential of leveraging social capital in community responses to emergency disasters remains under-researched (Meyer, 2018). Meanwhile, research involving emergency resource allocation in disasters has primarily focused on supplier selection (Hu et al., 2022), inventory optimization (Shehadeh and Tucker, 2022), warehouse location problems (Wang et al., 2021), and routing and scheduling (Caunhye et al., 2012). However, there is limited research on how to effectively distribute relief supplies to individuals within communities once they reach the disaster area.

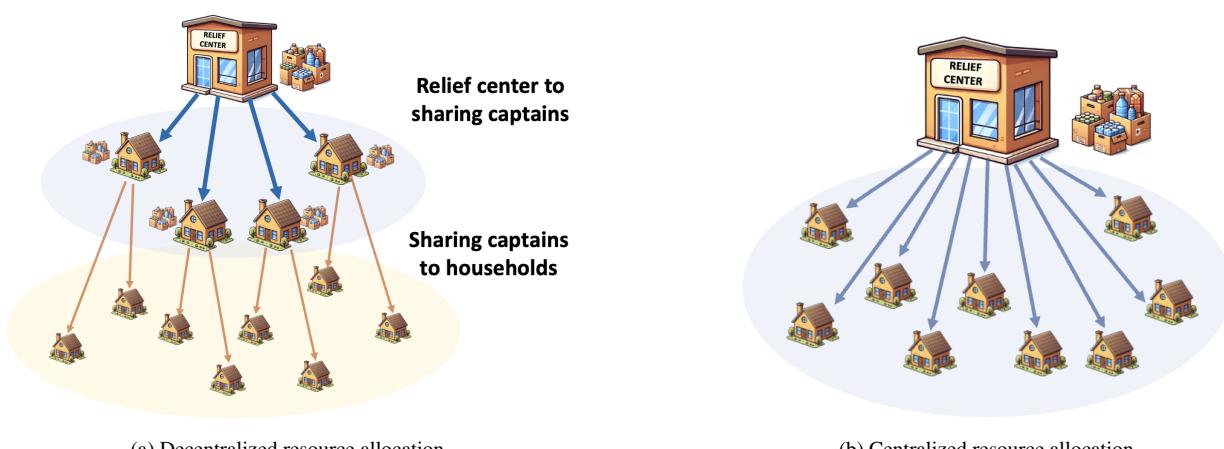


Figure 1: Centralized resource allocation and decentralized resource allocation

In this study, we are interested in leveraging place-based social capital to decentralize emergency resource allocation in communities. Specifically, based on the survey data of two communities in Seattle, Washington state, we propose a decentralized resource allocation strategy (as shown in Fig. 1(a)) leveraging place-based social capital. Different from traditional centralized resource distribution methods, where individuals queue at relief centers, the decentralized resource allocation strategy includes identifying several ‘sharing captains’ within the community, sharing captains obtain resources from the relief center and subsequently share them with other residents. The following questions will be answered in this study:

1. Compared to fixed-point distribution, to what extent can social-capital-based decentralized emergency resource allocation improve the emergency resource allocation practice?
2. Does the potential of social capital in emergency resource distribution vary across different communities?
3. If decentralized resource sharing model considering social capital proves effective, what recommendations can we offer for emergency supply distribution in community disaster scenarios?

The remainder of this paper is organized as follows. Section 2 introduces the study contexts of our research. Section 3 elaborates on the theoretical framework of the paper. Section 4 presents the experiment results, sensitivity analysis, and discussions. Section 5 discusses the conclusions, and Section 6 offers suggestions for community disaster response and preparedness.

2. Study Contexts

Seattle is one of the cities with the highest number of natural disasters in the United States, including winter storms, landslides, floods, and earthquakes (Joffe et al., 2013). Due to its location on the west coast of the Pacific Ocean, it is considered overdue for the Cascadia Subduction Zone earthquake, projected to range between 8.0 and 9.2 in magnitude (Kulkarni et al., 2013, Lindh, 2016). When it happens, the estimated direct fatalities for Oregon and Washington states are up to 10,000, with more than \$80 billion in economic losses (RWSPT, 2017). Tapping into the social capital to improve emergency relief coverage and response efficiency, helping people through the crisis, is our desideratum. Therefore, in 2018-2019, a survey was carried out across two distinct Seattle, Washington state, Laurelhurst, and South Park, whose geographic locations are shown in Fig. 2, to study community preparedness and willingness to share in the face of disasters.

When disaster strikes, community capital can be divided into material capital and social capital. Material capital is mainly reflected in resource inventory (Li et al., 2023), with different residents having varying levels of disaster preparedness (Zamboni and Martin, 2020, Wang et al., 2023a). The social capital of the entire community is a potential force we can utilize (Putnam, 1993), described as the intangible resource in relationships between people (Coleman, 1988). Many sociological literatures demonstrate how to assess a community’s social capital, including the existence and participation of community groups (Putnam, 1993, 2015), groups’ negative/positive perceptions of the community (Wasserman and Faust, 1994), the level of trust among citizens (Nakagawa and Shaw, 2004, Putnam, 2000), and the depth of social relationships (Center, 2000, Forbes and Zampelli, 2013). Therefore, the designed survey is divided into two modules. One focuses on people’s disaster preparedness, mainly resource reserves. We choose the resources most directly related to survival, such as water, food, warm clothing, medicine, and first aid, often distributed first in disasters (DEM, 2016). The other on people’s lives within the community, including sharing preferences, social ties, participation in public affairs, trust, and sense of belonging. The designed survey questions are shown in Table 1. These two communities have certain representativeness and differences to capture heterogeneous community characteristics and disaster preparedness. Specifically, Laurelhurst has one of the highest median household incomes and life expectancy for Seattle

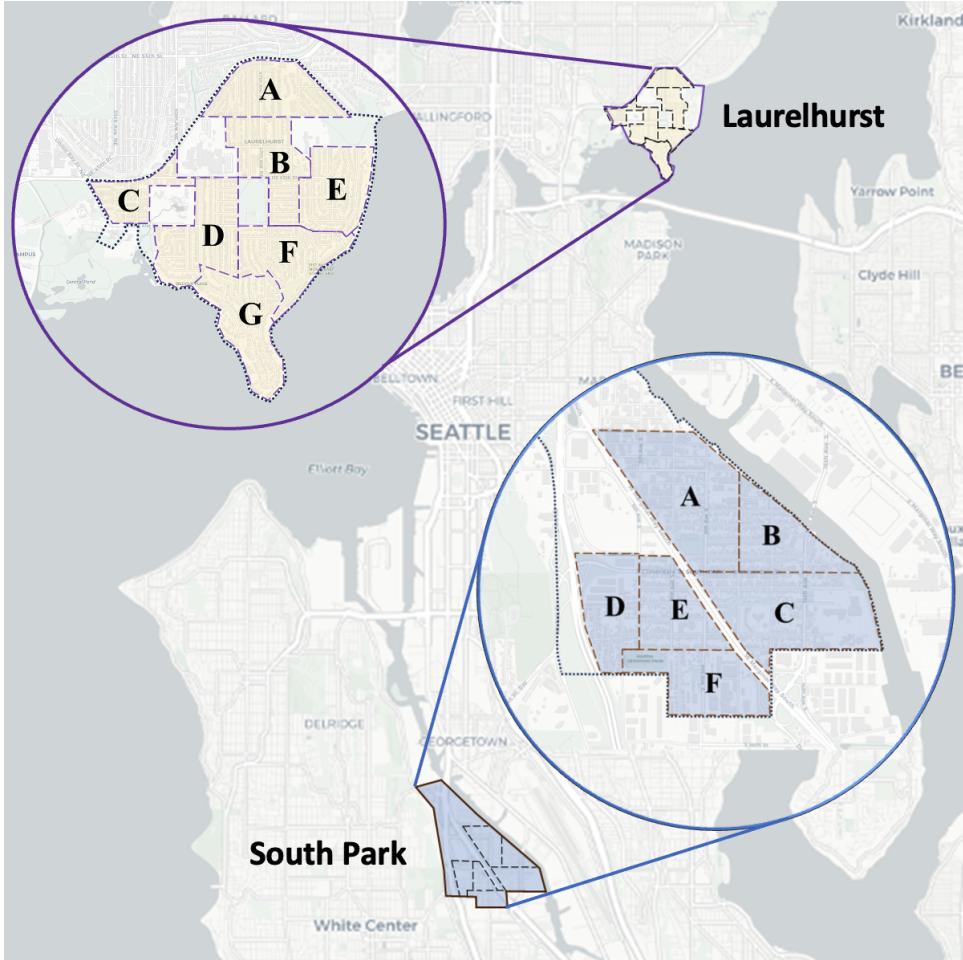


Figure 2: The geographic location of Laurelhurst and South park communities

residents and is made up mostly of white residents. In contrast, South Park is a racially diverse neighborhood, where 45% of residents are Hispanic or Latino, 50% of families speak English as a non-native language, and 25% of families live below the poverty line (Li et al., 2023). Questionnaires were randomly distributed to some households in Laurelhurst and South Park¹, and Fig. 3 and Fig. 4 show the survey responses of Laurelhurst and South park, respectively.

Attribution	Question
Resource inventory	How long your household is prepared to be on its own in the case of a disaster? (Regarding water, food, warm clothing, medicine, and first aid)
Sharing preferences	Assuming you had a one-week resource (water, food, medications, first aid supplies and warmth), with whom (nobody; family and close friends only; family, close friends, and acquaintances only; anyone in need) you be willing to share?
Trust	Do you agree or disagree with: “In general, you can trust people” ? (strongly agree; agree; no opinion; disagree; strongly disagree)
Belonging	Do you agree or disagree with: “I feel the community is a part of me” ? (strongly agree; agree; no opinion; disagree; strongly disagree)
Participation	How many hours did you spend participating in community activities with other people?
Social ties	How many close friends/family members and how many acquaintances (people you know on a first-name basis) do you have in each area?

Table 1: Survey questions

It can be seen that households in the community have different inventories. For Laurelhurst, around 40% of households have less than three days of stock for water, food, and medication and less than six days for first aid supplies and warmth. The situation is similar but worse in South Park. For trust and sense of community belonging, in Laurelhurst and South Park, about 80% of

¹The number of responses in Laurelhurst and South Park are 263 and 203, respectively.

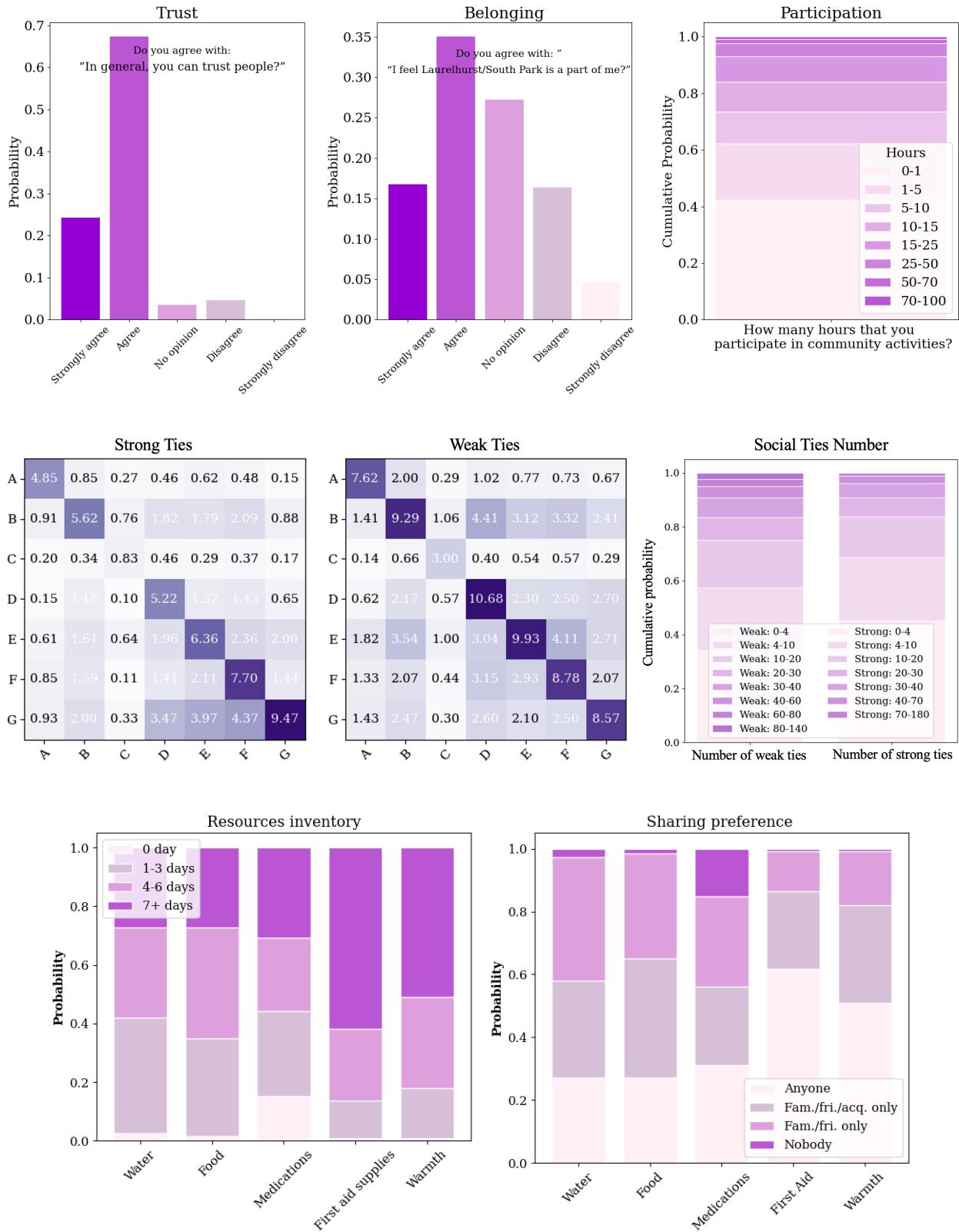


Figure 3: The survey responses of Laurelhurst neighborhood

people are willing to trust others, and more than half feel their community is part of them. About 30% of residents living in Laurelhurst devote more than 10 hours a week to community activities. In comparison, only about 20% of residents in South Park devote more than three hours a week. Regarding social ties, about 40% of residents have more than 10 weak social ties in Laurelhurst, and 20% have more than 30 weak social ties and more than 20 strong social ties. By contrast, less than 20% of residents have more than 12 weak social ties and more than 8 strong social ties in South Park. These indicate that the Laurelhurst community has more social connections and a stronger social network.

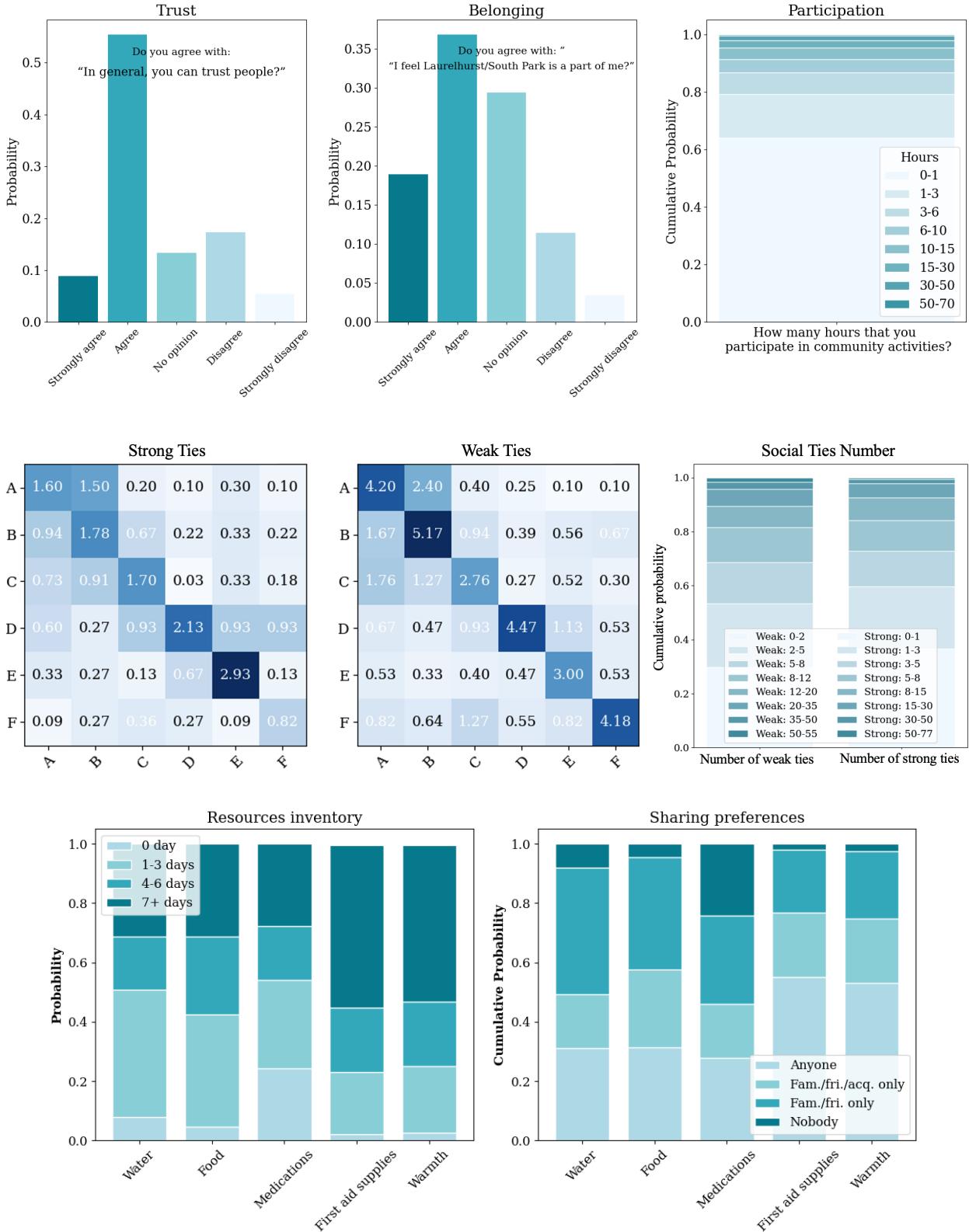


Figure 4: The survey responses of South park neighborhood

3. Methodological framework

The social capital of an entire community is a potential strength that we can tap into when disaster strikes (Uekusa et al., 2022). We propose a method for quantifying the community's social capital based on the survey data of community residents, and then we propose a decentralized resource allocation model and evaluate its performance. This section introduces the methodological framework of the paper, as shown in Fig. 5, comprising four main parts.

- **Community social network construction.** Quantify the community's social capital based on survey data, where households are represented as nodes, corresponding to different social capital values, and varying strengths of social ties indicated as edges. This network serves as the foundational structure for the implementation of decentralized resource sharing.

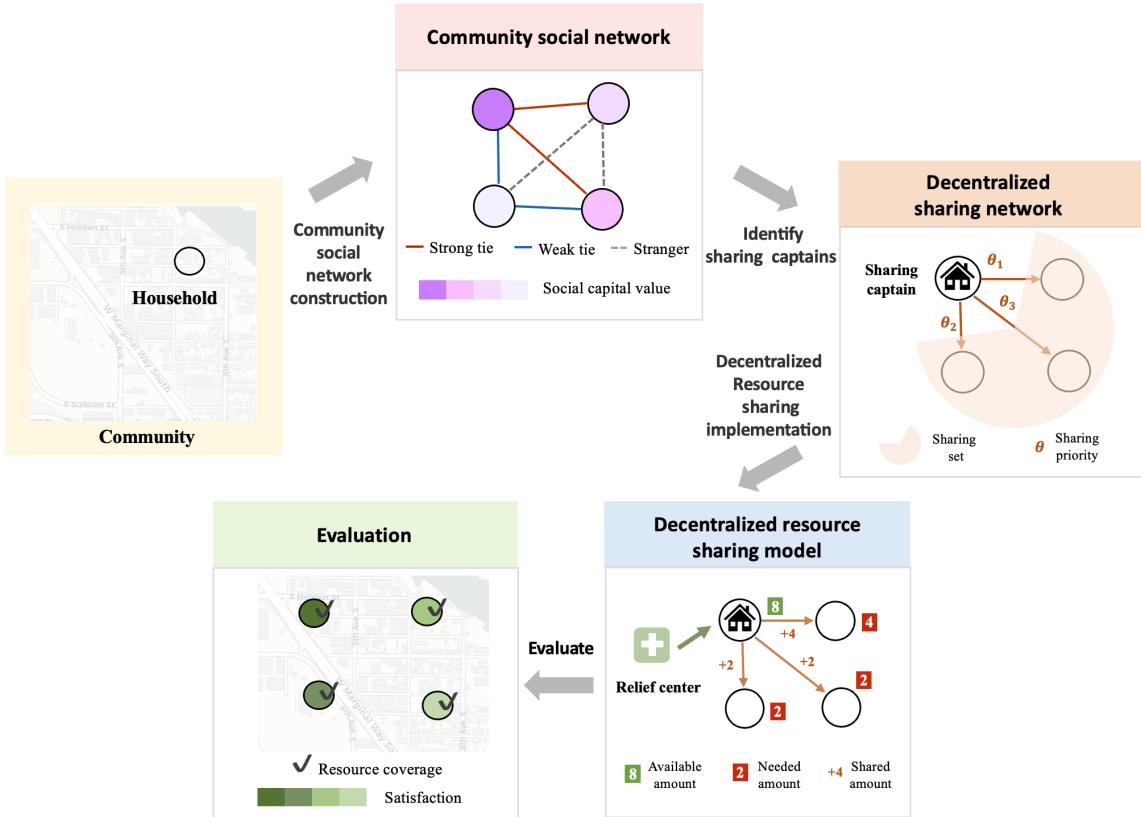


Figure 5: Methodological framework

- **Decentralized sharing network.** In this part, key households appointed as ‘sharing captains’ are identified based on their social capital values in the community social network. We define these captains’ sharing sets and priorities as the basis for analyzing their resource-sharing behavior during real disaster scenarios.
- **Decentralized resource sharing implementation.** This subsection elaborates on implementing the decentralized resource-sharing model, including the processes of sharing captains acquire resources from relief centers and distribute them within the community. A mixed integer linear programming problem is established to simulate the dynamics of resource sharing in real-world scenarios.
- **Evaluation.** The final part is about the assessment of the decentralized resource-sharing model. It introduces metrics to evaluate the resource coverage rate over time and community members’ satisfaction with the allocation process, aiming at understanding the model’s effectiveness.

3.1. Community social network construction

It is hard to know every individual’s information in a community, but responses to survey questionnaires through sampling allow us to glimpse the disaster preparedness and important social capital attributes of community residents, providing a basis for quantifying the community’s social capital. Since the social capital of a given area often follows some repeatable patterns (Newman et al., 2002, Liben-Nowell et al., 2005), we constructed a community social network $G = (N, E, A)$ based on known survey data, where N is a set of nodes, and each node represents a household; E is the set of social ties, if there is a social tie between node i and node j , then there is an edge e_{ij} , of which e_{ij}^S represent strong ties and e_{ij}^W represent weak ties; A_i stands for the social capital value of node i .

Step 1: Generate connection number o_i between nodes in the community network

We employed node degree distribution (Erdős et al., 1960, Barabási and Albert, 1999), commonly used in generating social networks (Liben-Nowell et al., 2005, Xu et al., 2022), to depict the probability of connection counts in the network, thereby generating the number of social links for each household. Assuming v is the number of social relations a family has, and V represents

the set of social ties derived from the survey results, the probability mass function of the negative binomial distribution and its log-likelihood function for v is:

$$P(v) = \frac{\Gamma(v+n)}{v! \Gamma(n)} p^n (1-p)^v \quad (1)$$

$$l(v; n, p) = \sum_{v \in V} [\log \frac{\Gamma(v+n)}{v! \Gamma(n)} + n \log p + v \log(1-p)] \quad (2)$$

where $\Gamma(\cdot)$ refers to the gamma function, while n and p are the parameters that need to be determined. For each community, the values of n and p can be obtained from the values of the maximum likelihood estimation parameter of the survey data.

Based on the node degree distribution obtained for the community, we generate the node degrees o_i ($0 \leq o_i \leq |N| - 1$) for all nodes within the community network, representing the number of their social ties with other nodes.

Step 2: Calculate the connection probabilities between all nodes

Considering the distance decay effect (Stutz, 1973, Bourgeois and Friedkin, 2001), where closer households have stronger social ties (Goldenberg and Levy, 2009), the social strength follows a power-law decay with geographic distance (Liben-Nowell et al., 2005, Xu et al., 2022), which can be described by:

$$p(d_{ij}; \gamma) \propto d_{ij}^{-\gamma} \quad (3)$$

where $p(d_{ij}; \gamma)$ represents the likelihood that a social connection exists between two nodes households i and j , based on the geographical distance d_{ij} between them, and γ is a parameter that needs to be determined. Since it is difficult to estimate every resident's social connections within the community, we generate the probability of households having social ties in each sub-area of the community based on Equation (3):

$$p_k^i(\gamma) = \frac{\sum_{j \in N_k \setminus \{i\}} p(d_{ij}; \gamma)}{\sum_{j \in N \setminus \{i\}} p(d_{ij}; \gamma)}, \quad \forall i \in N_{\text{sample}}, k \in K \quad (4)$$

where k denotes the regions within the community, as illustrated in Fig. 2; N represents all the households within the community; N_k is the set of households within region k ; N_{sample} refers to the households that were surveyed; $p_k^i(\gamma)$ signifies the anticipated proportion of social ties of household i in region k .

Further, based on survey results, we calculate the value of $\hat{\gamma}$ using the least squares method:

$$\hat{\gamma} = \underset{\gamma \in \mathbb{R}}{\operatorname{argmin}} \|\mathbf{P}(\gamma) - \mathbf{P}_{\text{survey}}\|^2 \quad (5)$$

where $\mathbf{P}(\gamma)$ and $\mathbf{P}_{\text{survey}}$, respectively, represent the observed and predicted proportions of social relationships among sampled families in different subareas of the community. Based on the probabilities of connections between nodes, for household i , other nodes are selected to connect with it until the node degree of i is satisfied. Subsequently, based on survey data, each household is allocated a proportion of weak and strong social ties, as shown in Fig. 3 and Fig. 4. Unconnected nodes in the network are considered strangers.

Step 3: Calculate residents' social capital values

We set a series of indicators a^z to represent each household's social capital attribute, including sharing preferences, trust, sense of belonging, participation, and number of social tie numbers. From Step 1, we obtain each household's number of social contacts with other households. For other attributes, based on survey data, we can obtain their probability distribution $P(a^z)$ in the community (see Fig. 3-4). Following the methods used in past research to measure the level of community social capital based on individual-level survey data (Graddy and Wang, 2009, Jordan et al., 2010), we randomly generate the values of a_i^z for each household i based on the correspond-

ing probability distribution. Additionally, we assign a weight w^z to each attribute and calculate the social capital value of each resident based on the following steps: (1): Normalize each indicator including a^z ; (2): Get the social capital value of each household: $A_i = \sum_{z \in \{Z_1, Z_2\}} w^z * a_i^z$. Based on that, we obtain the social-capital-based community network $G = (N, E, A)$.

3.2. Decentralized resource network

In this subsection, we develop the decentralized sharing network, which is the preliminary of the decentralized resource allocation approach, composing of sharing captains, their sharing sets, and their sharing priorities.

3.2.1. Sharing captains and sharing sets

The advantageous role of decentralized implementation in disaster relief efforts has been emphasized (Gunessee et al., 2018). The Federal Emergency Management Agency notes that in disasters, individuals closest to the affected areas are often the first to respond actively (FEMA, 2019). Our approach is grounded in the community social network, identifying certain households within the community to serve as sharing captains. Households with extensive social tie networks are equipped to aid a broader spectrum of individuals during disasters; concurrently, those who exhibit a stronger inclination towards public engagement, resource sharing, and trust in others are more predisposed to contribute significantly to distributing and sharing resources in emergencies (Jones and Faas, 2016, Choo and Yoon, 2022). Since social capital value consists of the weighted sum of social capital attributes according to Chapter 3.1, we select households from high to low according to the social capital value A_i to form a sharing captain set \mathcal{K} .

Although the practice of resource sharing is commonly embraced, differences in sharing preferences are observed (Kim et al., 2021), which is also revealed in Fig. 3 and Fig. 4. We define \mathcal{D}_i as the sharing set of families that captain i is willing to share resources with. For example, if the sharing preference of captain i is “family and close friends only”, the set \mathcal{D}_i includes all families with whom captain i has strong social ties; if the sharing preference of captain i is “family, close friends, and acquaintances only”, the set \mathcal{D}_i includes all families with whom captain i has strong social ties and weak social ties, like captain A and captain F, as shown in Fig. 6. It is worth noting that there may be overlap in willing sharing sets of different sharing captains because most people have more than one social tie in the community.

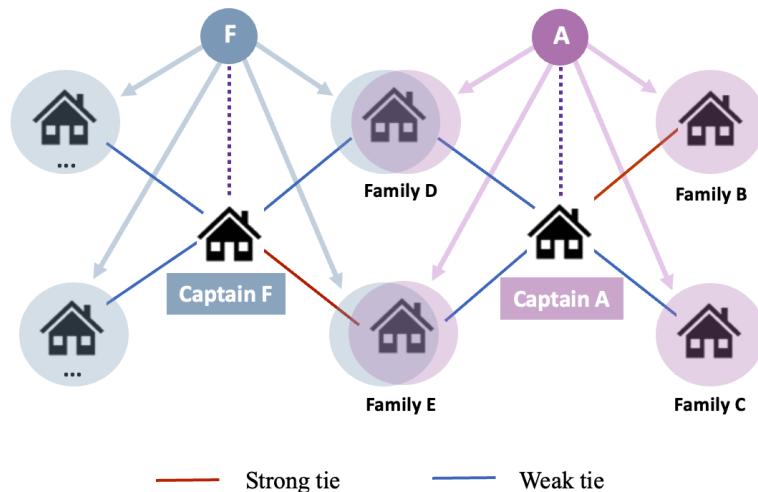


Figure 6: Illustration of decentralized sharing network

3.2.2. Sharing captains' sharing priority

During disasters, driven by emotional considerations, individuals are often more inclined to share with family and friends, those with whom they have strong social ties (Murphy, 2007, Schreiner et al., 2018); while on the rational side, their sense of responsibility prompts them to help the family that lacks resources and faces survival difficulties in the disaster as the humanitarian assistance (Rennemo et al., 2014, Huang et al., 2015). Therefore, we define the concept of

resource sharing priority $\theta_{ij} (\forall j \in \mathcal{D}_i)$, jointly determined by the number of resources that family j lacks and the social ties between family i and family j , indicating the priority of sharing captain i to share resources with family j in a real disaster response:

$$\theta_{ij} = \xi_1 * \hat{r}_j + \xi_2 * \hat{\epsilon}_{ij} \quad (6)$$

where \hat{r}_j represents the number of resources the household j lacks and $\hat{\epsilon}_{ij}$ is used to quantify the strength of social ties, they are both normalized. The weights of relational and resource-related factors satisfy $\xi_1 + \xi_2 = 1$.

The number of resources that household j needs (r_j): The survey responses (Fig. 3 and Fig. 4) reveal the varying levels of resource inventory among residents, based on which we can simulate the resource inventory q_i of each household in the community at the initial stage of the disaster according to the inventory distribution obtained from survey data. Assuming that the estimated lockdown time of the community is τ , usually given by the emergency response department and after which people can normally obtain daily necessities, we can simulate the number of resources each family needs, $r_i = \max(\tau - q_i, 0)$.

The strength of social ties between families i and j (ϵ_{ij}): Research indicates that sharing priorities or willingness diminish with the weakening of social relationships (Schreiner et al., 2018, Strombach et al., 2014). Referring to the approach of Li et al. (2023) that allocates different weights to different social ties, we assign distinct values to quantify the influence of various social relationships in determining the priorities for sharing resources:

$$\epsilon_{ij} = \begin{cases} 3, & \text{if families } i \text{ and } j \text{ have a strong tie} \\ 2, & \text{if families } i \text{ and } j \text{ have a weak tie} \\ 1, & \text{if families } i \text{ and } j \text{ are strangers} \end{cases} \quad (7)$$

3.3. Decentralized resource sharing model

Informal community leaders who possess a deep understanding of their residents are often more engaged in disaster response efforts (FEMA, 2011). In the decentralized resource sharing model we propose, these sharing captains assume such roles, acquiring resources from relief centers and sharing them with other households, as shown in Fig. 7(a).

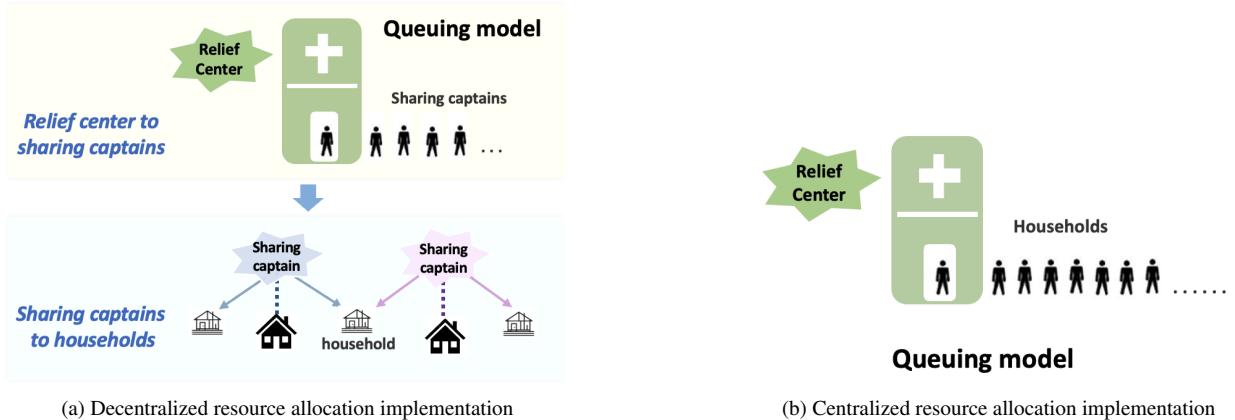


Figure 7: Comparison of decentralized and centralized resource allocation implementations

3.3.1. Relief center to sharing captains

The conventional method of resource distribution often involves fixed-point distribution (FEMA, 2015), where individuals queue at relief centers to obtain resources, as shown in Fig. 7(b). Ozen and Krishnamurthy (2018, 2022) model the process of residents queuing at relief centers for resource acquisition using queuing network theory. Although our focus is more on decentralized distribution driven by the social capital inherent within communities, the behavior of sharing captains collecting resources from relief centers can still be simulated using the queuing model. We

assume that there is one service node in the relief center, as shown in Fig. 8. We employ a Poisson distribution to simulate the arrival of sharing captains at the relief center, with an arrival rate of λ and a service rate at the relief center of s , following an exponential distribution. Based on the queuing network theory (Bose, 2013), the average time for each sharing captain to receive resources is $W_s = \frac{1}{s-\lambda}$.

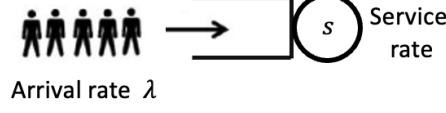


Figure 8: Queuing model of sharing captains at relief center

3.3.2. Sharing captains to households

Before going into details of sharing captains’ sharing process, we make some necessary assumptions underlying the social-capital-based resource-sharing behavior in community: (1) After receiving resources from the relief center, the sharing captains will share resources, except those they need, with other families in the community, and the rest will be returned to the relief center; (2) Considering the relief materials usually are scarce initially, each family receives no more resources than they need.

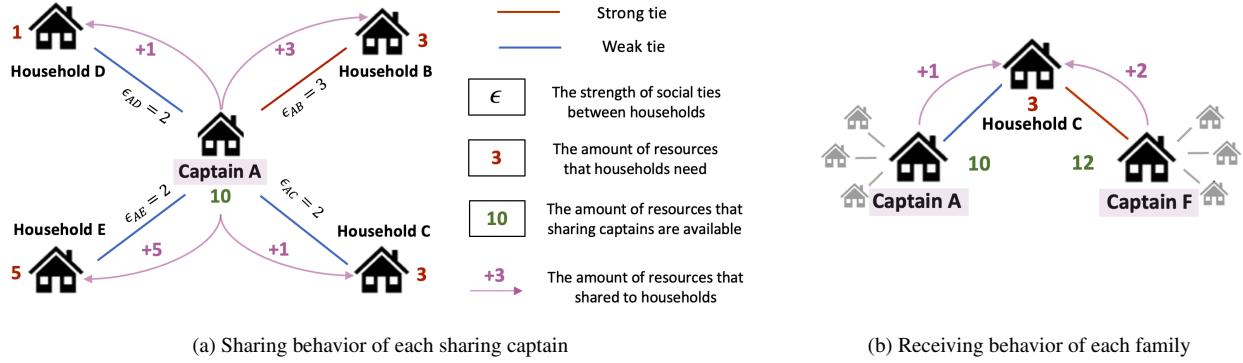


Figure 9: Social-capital-based resource sharing-receiving behavior in the community

We utilize a simplified example to elucidate the sharing behavior of sharing captains, as depicted in Fig. 9(a). Assume that household A, with a sharing preference encompassing “family, close friends, and acquaintances” is designated as a sharing captain. For simplicity, we posit that this set comprises only households B, C, D, and E. Further, we compute the sharing priority of Captain A towards each household within its sharing set to simulate its sharing behavior in real scenarios. We assume the rational and resource-related factors to be 0.5, which mirrors one realistic situation where Captain A would contemplate both the resource reserves of households B, C, D, and E and the intensity of their social ties to determine the sequence of resource-sharing. In this instance, the priority ranking of Captain A’s sharing with each household is: $\theta_{AE} > \theta_{AB} > \theta_{AC} > \theta_{AD}$. However, given the typical resource scarcity during disasters, the relief center’s allocation to each sharing captain is finite (Su et al., 2016). Therefore, it is pivotal to note that the total resources available for distribution by Captain A might not suffice to meet the demands of all households in its sharing set. As illustrated in Fig. 6, overlaps exist among the sharing sets of different sharing captains due to the intertwined nature of social ties within the community. Suppose household C is also part of another sharing captain’s set, as shown in Fig. 9(b). In that case, Captain F could also allocate a portion of its resources to household C, and one possible resource allocation situation based on this scenario is shown in Table 1.

In the real world, decentralized resource sharing by sharing captains is more intricate than our illustrative example, given their extensive social ties. To simulate the resource-sharing of sharing

Household	B	C	D	E
Captain A	3	1	1	5
Captain F	-	2	-	-
Resource coverage situation	✓	✓	✓	✓

Table 2: The number of resources that sharing captains share with each family

captains, we present the following model formulation:

$$\max \sum_{i \in \mathcal{K}} \sum_{j \in \{N|\mathcal{K}\}} \theta_{ij} x_{ij} \quad (8)$$

$$\sum_{j \in \mathcal{D}_i} x_{ij} \leq Q_i - r_i, \quad \forall i \in \mathcal{K} \quad (9)$$

$$\sum_{i \in \mathcal{K}} x_{ij} \leq r_j, \quad \forall j \in \{N|\mathcal{K}\} \quad (10)$$

$$x_{ij} \geq 0, \quad \forall i \in \mathcal{K}, \forall j \in \{N|\mathcal{K}\} \quad (11)$$

where x_{ij} represents the amount of resources that sharing captain i gives to family j , and Q_i represents the amount of resources that captain i receives at the relief center.

In the model, the objective function (7) is designed to maximize the total amount of resources that each sharing captain shares with the families in the community, taking into account their sharing priorities. Equation (8) ensures that the amount of each resource shared by the sharing captains do not exceed the amount of the corresponding resources they obtain from the relief center minus the amount of their own resources required. Equation (9) requires that the amount of each resource received by each household does not exceed what they need. Equation (10) is a non-negative constraint on the variables. We use \mathcal{F}_i to represent families that receive resources from sharing captain i ($\mathcal{F}_i = \{j | x_{ij} > 0\}$), the order of which can be obtained according to the sharing priority of captain i . Assuming the sharing captain's resource sharing rate is u , following the exponential distribution, we can obtain the time t_j for each family j when receiving resources.

3.4. Evaluation of resource allocation scheme

To measure the performance of the decentralized resource allocation model, we define the two metrics:

(1): T time resource allocation coverage rate:

We calculate the resource distribution coverage for different time periods T as:

$$C_t = \frac{\sum_{i \in N} I_i(T)}{|N|} \quad (12)$$

where $I_i(T)$ is an indicator function, indicating whether family i received the resource before time T :

$$I_i(T) = \begin{cases} 1, & t_i \leq T \\ 0, & t_i > T \end{cases} \quad (13)$$

(2) Time perception satisfaction:

Perception is the result of people's subjective feeling and cognition, which is based on the limited rationality (Kahneman and Tversky, 1984), and victims with limited rationality are sensitive to rescue time in the process of emergency relief (Huang et al., 2012). During disasters, victims often have an urgent need for relief supplies and hold a psychological expectation regarding the arrival time of these resources. Drawing on the method proposed by Wang et al. (2023b), which calculates the time perception satisfaction of disaster victims based on the arrival time of relief resources and varying disaster conditions, we define the time perception satisfaction of each household as



(a) Laurelhurst community (b) South park community

Figure 10: Social ties network of two communities

follows:

$$f(t_i) = \begin{cases} 1, & 0 < t_i \leq t_0 \\ e^{-0.5[(t_i-t_0)/t_0]^{\alpha_i}}, & t_i > t_0 \end{cases} \quad (14)$$

where t_0 is the expected time of households and α_i represents the degree of urgency perceived by different victims regarding their needs, related to the amount of resources that families need. When the time to obtain resources is less than or equal to the expected time, people's time perception satisfaction is 1; when the time exceeds the expected time, the longer the waiting time, the lower the satisfaction. We set $\alpha_i = \alpha * r_i (\alpha > 0)$, where a higher value of α_i indicates a greater sensitivity of the victims to the arrival time of the supplies, leading to a more rapid decline in expected time satisfaction. The average satisfaction of all families in the community is:

$$S = \sum_{i \in N} f(t_i) \quad (15)$$

4. Experiment Results

In this section, we present the results of the social-capital-based community network construction described in Chapter 3, using the Laurelhurst and South park communities as examples. In addition, the decentralized distribution model considering social capital is compared with the traditional centralized distribution scheme to compare the resource coverage and residents' satisfaction under different distribution methods.

4.1. Detailed results of the social-capital-based community network construction

Community	n	p	$\hat{\gamma}$
Laurelhurst	0.7877	0.0256	-1.35
South park	0.8266	0.0669	-1.43

Table 3: The parameters of social-capital-based network construction in two communities

Following Step 1 and Step 2 of Chapter 3.3, we obtain the values of the parameters n and p for the node degree of the negative binomial distribution through the values of the maximum likelihood estimation parameter of the survey data. Additionally, we determined the social connection probability parameters $\hat{\gamma}$ for both the Laurelhurst and South Park communities, as detailed in Table 2. Subsequently, utilizing these parameters, we construct the community social networks for Laurelhurst and South Park communities, as depicted in Fig. 10. It is revealed a notable difference in the number of strong and weak ties within these communities. Specifically, the Laurelhurst community exhibited a significantly higher number of strong ties (10,452) and weak ties (14,564), in contrast to the South Park community, which had 2,249 strong ties and 5,143 weak ties. The number of

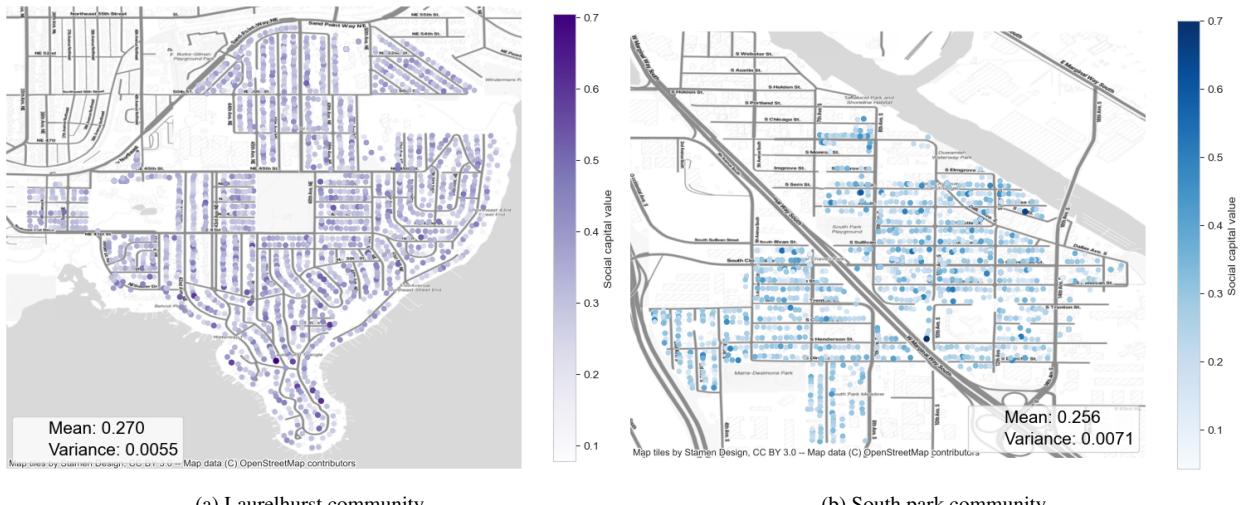


Figure 11: Social capital value of two communities

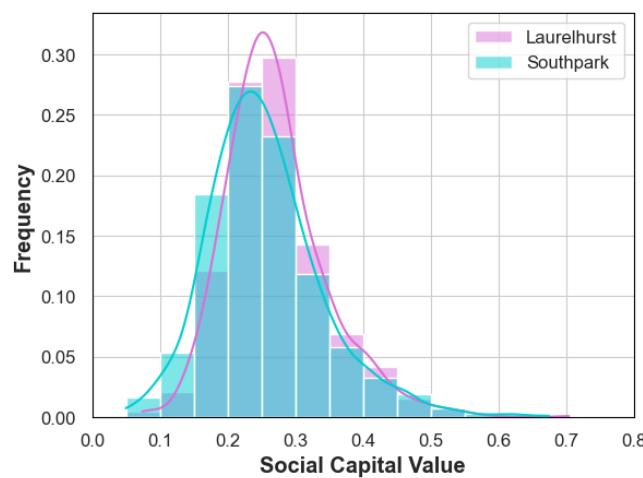


Figure 12: Social capital value distribution of two communities

strong social ties in Laurelhurst is approximately five times that of the South Park community, and the number of weak social ties is about three times as many.

Further, following Step 3, we calculated social capital values for households within these communities, representing each household's potential contribution and capacity to support the community during a disaster. The exploration by [Choo and Yoon \(2022\)](#) demonstrated that civic engagement and trust influence residents' ability to respond to disasters. In the research by [Li et al. \(2023\)](#) on community disaster resilience based on peer-to-peer sharing, the significance of social tie number and sharing preference in community disaster response was proven. Therefore, we highlight the significance of social tie number and sharing preference of households and set $w^z = \{2, 2, 1, 1, 1\}$ as the weight of sharing preference, social tie number, trust, belonging, and participation to calculate the social capital value of residents the two communities, as shown in Fig. 11. It can be seen that the average social capital value of residents in the Laurelhurst community is higher than that of South park, and the variance is smaller. At the same time, we calculate the frequency distribution curve of the social capital value of residents in the two communities, as shown in Fig. 12. It is shown that the Laurelhurst community's distribution skews to the right compared to the South Park community's, indicating that residents in the Laurelhurst community have a stronger social ties network and a higher sense of community mutual assistance in the face of disaster.

Subsequently, we set the number of sharing captains as $|\mathcal{K}| = 100$ and draw the distribution of sharing captains and their social ties in two communities, as shown in Fig. 13. It can be seen that the strong social ties of sharing captains in Laurelhurst account for 39.52% of all the strong social ties in the community, and the weak social ties account for 40.39% of all the weak social ties in the community. In comparison, the strong social ties and weak social ties of the South park community sharing captains account for 51.67% and 48.22% of the total, respectively, because the

total number of social ties there is lower.

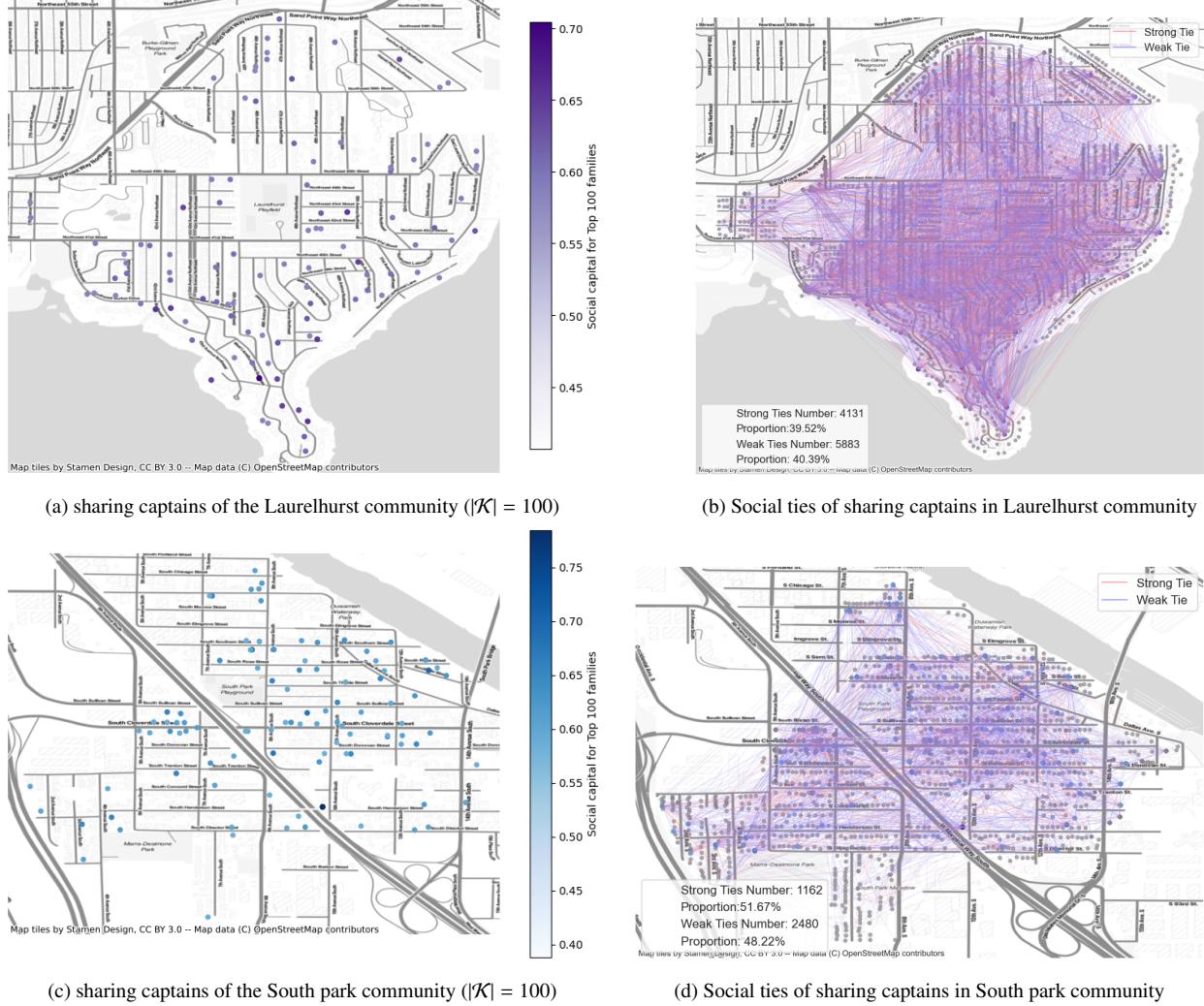


Figure 13: sharing captains in two communities

4.2. Evaluation of the decentralized resources allocation model

In Chapter 4.2, we delineate the decentralized resource allocation model around the sharing captains. The number of sharing captains is a critical factor influencing the efficacy of the resource distribution mechanism. A limited number of sharing captains could lead to prolonged wait times for resources among community residents, thereby diminishing the model's efficiency. Conversely, an excessively high number of sharing captains might result in a scenario where many families, acting as captains, experience significant wait times at relief centers, rendering the approach similar to a centralized distribution model. Therefore, we set the number of sharing captains $|\mathcal{K}|$ to change within a certain range, explore the impact of the number of sharing captains on the average satisfaction of residents, and compare it with the centralized distribution scheme. Relevant parameters are set as follows: The weights of relational and resource-related factors that comprise sharing priority are set as $\xi_1 = \xi_2 = 0.5$. In the centralized distribution scheme, residents line up at the relief center to receive resources, following the process depicted in Fig. ???. Referring to the setting of [Ozen and Krishnamurthy \(2022\)](#) about relief distribution during the 2015 Nepal earthquake, we model the arrival time for people arrive time of people at the relief center as a Poisson distribution, with an arrival rate of $\lambda_c = 2 \text{ families / per minute}$. The service rate of the relief center team is modeled as an exponential distribution, with a service rate of $s_c = 1 \text{ family / per minute}$. Given that the decentralized distribution scheme involves only the sharing captains traveling to the relief center and these captains require additional time for information verification and to collect more resources for distribution among other residents, we adjust the arrival and service rates to $\lambda_d = \omega * \lambda_c, s_d = \omega * s_c$, respectively, where ω is a speed proportional factor set at 10. After obtaining resources, the rate at which sharing captains distribute them to other families is modeled as an exponential distribution, with $s_H = 1 \text{ family / per 20 minutes}$. Additionally, the sensitivity

of the expected rescue time to the resources urgency is set at $\alpha = 1$, and the lower limit of the expected rescue time is set as $t_0 = 600$ (minute).

We run the implementation 100 times and average the results, as shown in Fig. 14. It is observed that the average satisfaction of residents initially increases and then decreases with the number of sharing captains, a trend consistent across both communities. Notably, when the number of sharing captains is in the range of 50-80, both communities are close to achieving the highest level of resident satisfaction. Comparative analysis with the centralized distribution scheme revealed that the decentralized distribution scheme significantly enhances average satisfaction in the Laurelhurst community, with a peak improvement rate of approximately 61.3%. Consequently, the improvement rate in the South Park community under the decentralized scheme was lower, peaking at nearly 19.1%. This is mainly attributed to the smaller population in the South Park community, exhibiting shorter waiting times at the relief center under the centralized scheme, resulting in relatively higher average satisfaction.

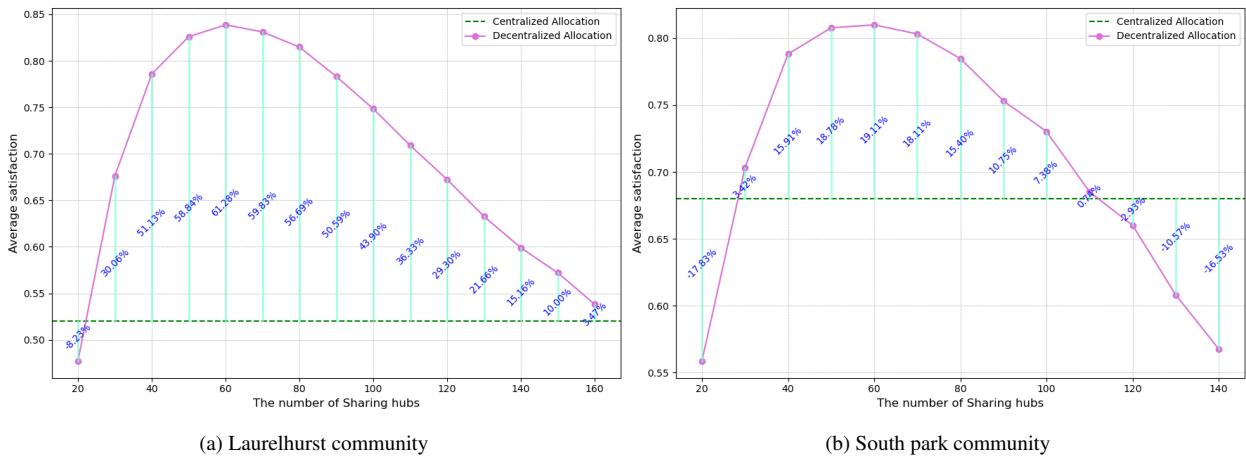


Figure 14: Satisfaction rate of decentralized and centralized resource allocation

Then, we analyze the differences in resource coverage over time between the centralized and decentralized allocation schemes. A key objective of the decentralized resource allocation model was to improve resource accessibility, particularly for community segments such as the elderly and severely injured, who are unable to visit relief centers. Setting the number of sharing captains in Laurelhurst and South Park at 60 (corresponding to the highest satisfaction level as shown in Fig. 14) and varying the proportion of people without resource access k , we plotted the resource coverage curves for different values of k under both schemes. As illustrated in Fig. 15, the decentralized resource allocation scheme ensures comprehensive resource accessibility within the community, facilitated primarily through some sharing captains that distribute resources even to strangers besides those within their social networks. The decentralized resource allocation scheme also achieves more rapid and extensive resource coverage compared to the centralized approach, whose effectiveness diminishes as the proportion of inaccessible residents increases. Simultaneously, we investigated the dynamics of resource sharing within the Laurelhurst and South Park communities, focusing on whether resources were predominantly shared through strong ties, weak ties, or with strangers. The findings, presented in Table 3, indicate that in Laurelhurst, a substantial portion of resource sharing occurs through strong ties, reflecting the community's dense social network. In contrast, South Park, characterized by a less dense social network, witnesses a majority of its resources being shared through both strong and weak ties, with a minor fraction being shared by strangers.

Community	# from strong ties	# from weak ties	# from strangers
Laurelhurst	67.42 %	19.40 %	13.18 %
South park	40.95%	42.56 %	16.50 %

Table 4: The proportion of resources shared through different social ties in two communities

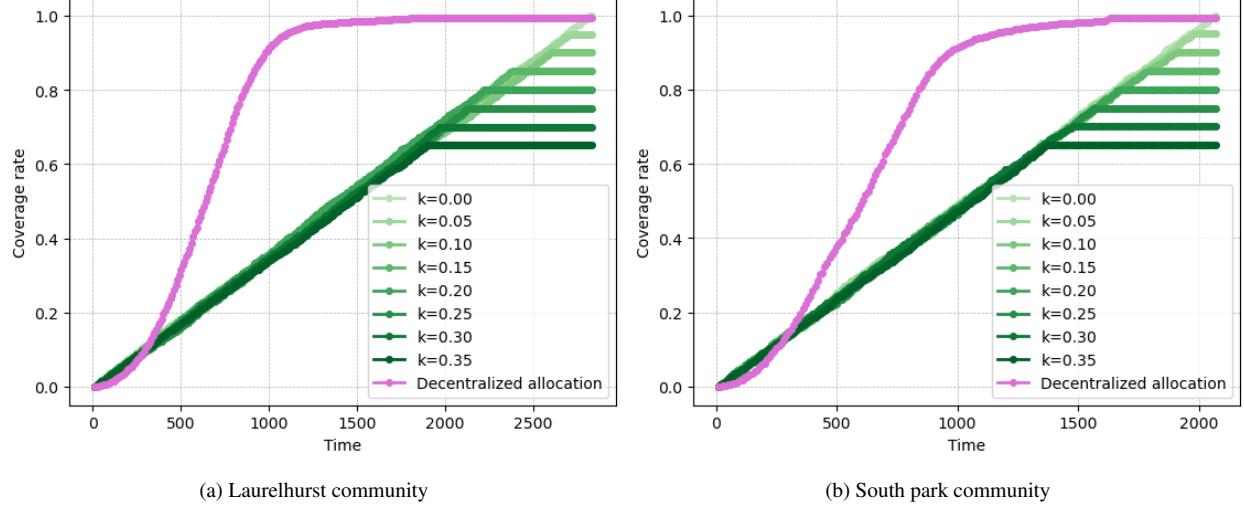


Figure 15: Coverage rate of decentralized and centralized resource allocation

4.3. Sensitivity analyses

In this section, we delve into the factors influencing decentralized resource allocation, encompassing residents' sharing preferences, the number of social ties in the community, the sharing priorities of sharing captains, and the rescue time of emergency resource allocation within the community.

4.3.1. Sharing preference

Sharing preference is an important factor affecting the decentralized distribution scheme because the sharing sets of each sharing captain are divided according to their sharing preference, as mentioned in Chapter 4.1. We represent the sharing preference of people in the community as $[a,b,c,d]$, where 'a', 'b', 'c', and 'd' correspond to the proportion of individuals unwilling to share with anyone, willing to share only with those having strong social ties, willing to share with both weak and strong social ties, and willing to share with everyone, respectively. the proportion of individuals unwilling to share with anyone, willing to share only with those having strong social ties, willing to share with both weak and strong social ties, and willing to share with everyone, respectively.

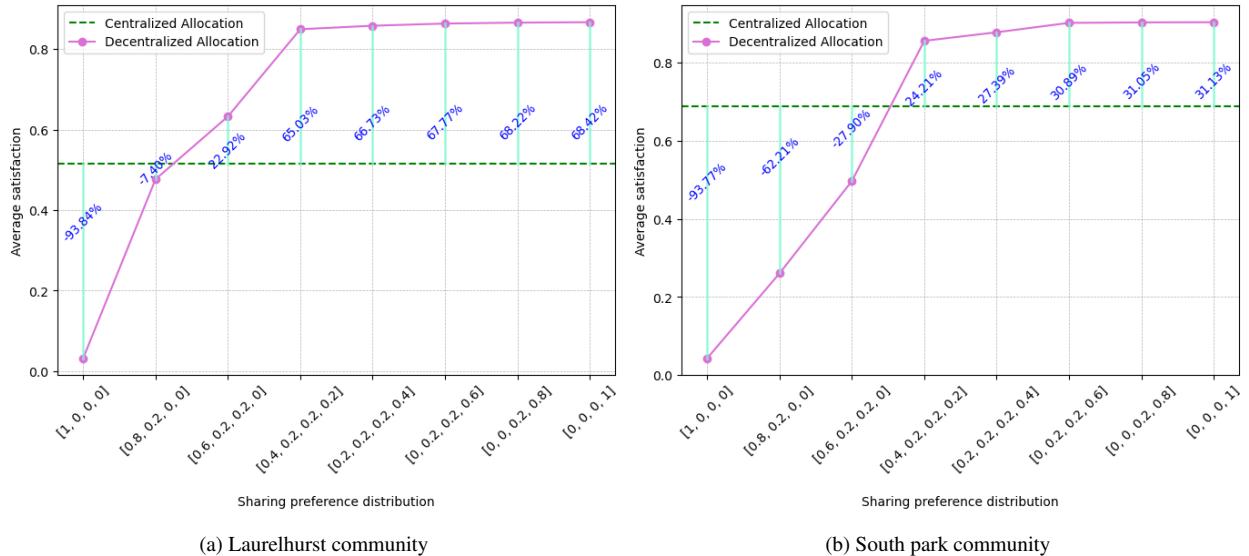


Figure 16: Satisfaction rate under different sharing preference distribution

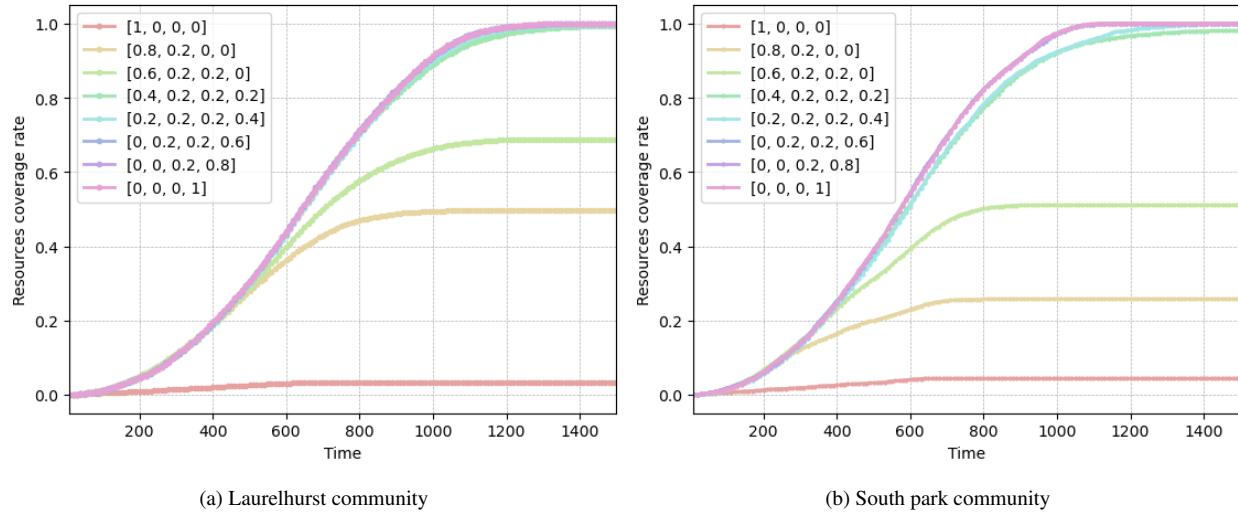


Figure 17: Resource coverage rate under different sharing preference distribution

As shown in Fig. 16, both communities show the same trend, with average satisfaction with decentralized distribution schemes increasing as a larger percentage of people are willing to share with more people. It can be seen that both communities exhibit a similar trend: the average satisfaction with the decentralized distribution scheme increases as a larger proportion of the population becomes willing to share with more people. A notable inflection point is observed when the distribution of residents' sharing preferences reaches [0.4, 0.2, 0.2, 0.2]. Prior to this point, an increase in the willingness to share among community members significantly enhances the average satisfaction level, rising from below 10% (when no one is inclined to share) to over 80% (when 20% of residents are willing to share with strong ties, both strong and weak ties, and everyone, respectively). Beyond this point, even as the proportion of those willing to share with more people increases, the growth in average community satisfaction becomes gradual and less pronounced. Comparing the Laurelhurst and South park communities, while the overall trend is consistent, the increase in average satisfaction is more pronounced in Laurelhurst. For instance, even with a sharing preference of [0.8, 0.2, 0, 0], Laurelhurst's average satisfaction (around 49%) significantly exceeds that of South Park (around 24%). This disparity can be attributed to Laurelhurst's denser network of strong social ties, which enhances resource coverage and satisfaction when only a minority is inclined to share exclusively with strong ties. This observation prompts further exploration into the impact of the number of social ties on decentralized resource allocation, as discussed in Section 4.2.2.

Furthermore, as illustrated from Fig. 17, the resource coverage within the community varies under different sharing preference distributions. In scenarios where no one is willing to share, the appointment of sharing captains becomes redundant. As the community's sharing preference distribution shifts from $[0.6, 0.2, 0.2, 0]$ to $[0.4, 0.2, 0.2, 0.2]$, there is a marked increase in resource coverage, from approximately 50% to nearly 95% for South park and from about 69% to nearly 98% for Laurelhurst. This increase aligns with the significant rise in residents' average satisfaction at the $[0.4, 0.2, 0.2, 0.2]$ distribution, as depicted in Fig. 16. While the sharing preference distributions used in this sensitivity analysis are hypothetical and may not precisely mirror real-world scenarios, the simulation underscores a crucial insight: In the proposed decentralized resource-sharing model, it is essential for a segment of the population to be willing to share with the majority. However, achieving an ideal state where everyone is willing to share with everyone else is not a prerequisite for the scheme's success.

4.3.2. Social ties number

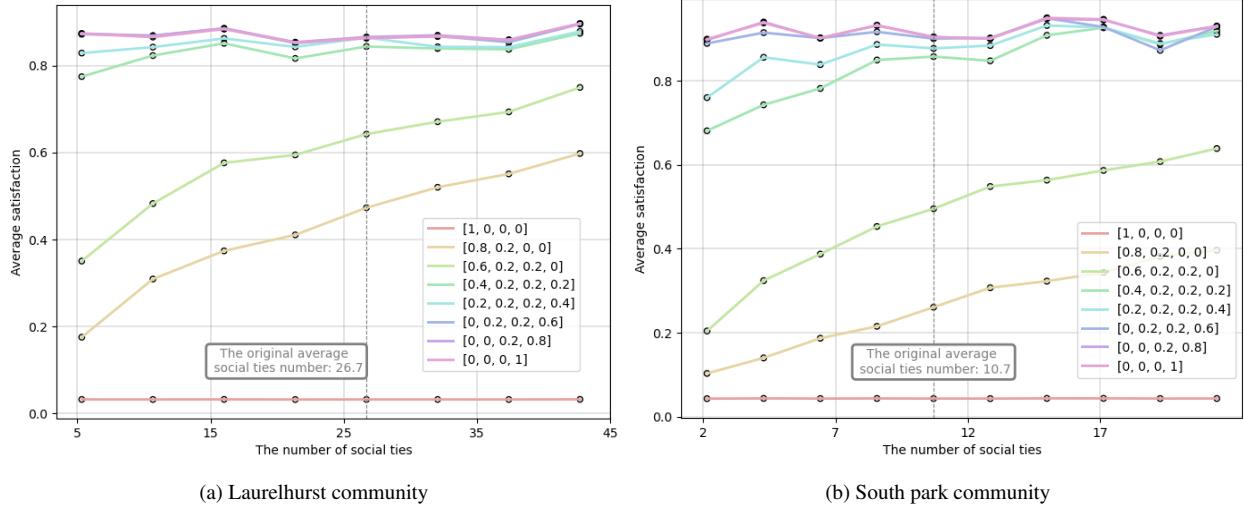


Figure 18: Satisfaction rate under different social ties number ratio

Further, we investigated the influence of social ties on average satisfaction by varying the number of social ties during the generation of social networks, as depicted in Figure 17. The findings indicate that the number of social ties exerts a limited influence on average resident satisfaction. In scenarios where the sharing preference is [0, 0, 0, 1], and thus no inclination to share exists, an increase in the number of social ties does not affect average satisfaction. In sharing preference distributions such as [0.8, 0.2, 0, 0] and [0.6, 0.2, 0.2, 0], where the community's willingness to share is relatively low, the addition of more social ties proves beneficial, facilitating resource access for more individuals and thereby enhancing average satisfaction. However, when a portion of the community is willing to share with everyone, as in distributions like [0, 0.2, 0.2, 0.6] and beyond, the increase in social ties does not significantly elevate average satisfaction. Interestingly, the study observed fluctuations in average satisfaction with the increase in the average number of social ties per resident, suggesting that a higher number of social ties is not invariably conducive to decentralized resource allocation. This observation is consistent with the findings of Choo and Yoon (2022), who investigated the relationship between disaster response capabilities and community social capital in Seoul, South Korea, and found that informal social networks were not a primary factor in disaster response effectiveness.

4.3.3. Sharing priority

The dynamics of resource allocation, influenced by the sharing priority of each captain, is another critical aspect of this study. Sharing priority, subjective to each sharing captain, affects the order in which resources are allocated to other families. In this study, we consider that the priority consists of two parts: relational-related factor (ξ_1) and resource-related factor (ξ_2). We varied the weight of these two factors from [0,1] to [1,0], representing a spectrum from completely rational to completely emotional decision-making of sharing captains. The impact of these variations on community average satisfaction is presented in Table 4.

Community	relational-related and resource-related factors	Average satisfaction	Reduction
Laurelhurst	[0,1]	85.14%	0
	[0.5,0.5]	84.15%	-0.99%
	[1,0]	82.53%	-2.61%
South park	[0,1]	86.76%	0
	[0.5,0.5]	85.78%	-0.98%
	[1,0]	85.61%	-1.15%

Table 5: Average satisfaction under different perceptual and rational factors in two communities

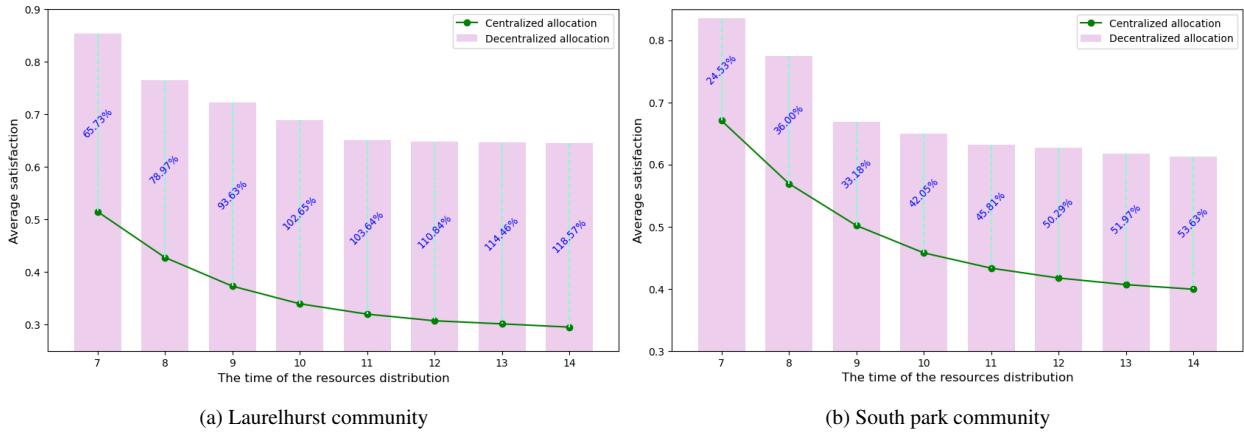


Figure 19: Satisfaction rate of decentralized and centralized resource allocation under different rescue times

The analysis reveals that maximum average satisfaction among residents in both communities is achieved when all sharing captains prioritize the scarcity of resources in other households for resource allocation. This outcome can be attributed to the fact that resident satisfaction during disasters is influenced not only by the timeliness of resource delivery but also by the urgency of resource needs. On the other hand, when sharing captains prioritize the strength of social ties over the scarcity of resources for distribution, the average satisfaction in both communities decreases, however, not drastically. This decrease is due to the potential neglect of households in urgent need of resources. Specifically, for the Laurelhurst community, the reduction in satisfaction is approximately 2.61%, while for the South Park community, it stands at about 1.15%. When sharing captains consider both social ties with those families and the resource situation of those families, the average community satisfaction falls in between the two extremes.

4.3.4. Rescue time

Rescue time is also a factor affecting residents' satisfaction. We varied the rescue time to explore the satisfaction differences between decentralized and centralized rescue plans. The results indicate a downward trend in community satisfaction as the rescue time lengthens. It is primarily due to delayed resource delivery, diminishing residents' available resources, and increasing urgency for resource replenishment. However, it is noteworthy that the decentralized distribution plan achieved significant and stable improvements across different rescue times in both communities, demonstrating the robustness of the decentralized distribution plan considering social capital. This observation highlights the importance of valuing the social capital within communities, which stimulates peer-to-peer sharing among residents, particularly when external rescue operations are delayed, with a higher satisfaction improvement rate.

5. Conclusion

This study explored the distribution of emergency supplies during the last mile of disaster response, focusing on leveraging peer-to-peer sharing driven by community social capital. First, we propose the methodology about constructing the social-capital-based community network, including data design, data analysis and network construction – serving as a foundation for evaluating community social capital. Subsequently, we introduced the decentralized resource allocation scheme. This scheme involves the identification of sharing captains within the community and the detailed process of resource reception and distribution by these captains. Finally, we evaluate the resource allocation scheme, focusing on two key metrics: the rate of resource coverage and the level of residents' satisfaction.

Our experiments and sensitivity analysis yielded several findings:

The feasibility of the decentralized resource allocation scheme.

- (1) Compared to traditional centralized allocation methods, the decentralized approach resulted in higher average satisfaction within both communities. Notably, the performance of the decentral-

ized scheme is influenced by the number of sharing captains: few are inefficient, leading to longer waiting times, while too many make it scarcely distinguishable from the centralized approach. For communities the size of Laurelhurst (1,873 households during our survey) and South Park (1,739 households during our survey), the ideal range is 50-80 captains.

(2) The decentralized resource allocation scheme enables 100% resource coverage in a shorter time frame than traditional methods, even for households unable to access relief centers due to injuries or age, underscoring the importance of community willingness to share and the established social ties.

Decentralized allocation isn't universally optimal.

From the sensitivity analysis, the state of social capital within a community influences the effectiveness of a decentralized distribution scheme, as reflected in residents' average satisfaction and resource coverage rates. The most direct factor influencing the decentralized resource allocation strategy is the residents' sharing preference. We can see that: (1) A community where the majority are unwilling to share with others is unsuitable for a decentralized distribution approach. (2) Having a minority within the community willing to share resources with the majority is vital for implementing a decentralized resource allocation scheme. However, it is not necessary to achieve an ideal state where everyone is willing to share, which is also hard to achieve. (3) The number of social ties within the community has a limited role in implementing the decentralized resource allocation scheme, being beneficial primarily when only a minority is willing to share.

The sharing priority of sharing captains isn't as critical as we assume.

When sharing captains make decisions on the order of resource sharing, comparing absolute resource demand priority with absolute relationship priority, although the overall community satisfaction is higher when the resource demand is prioritized, the difference is minimal. Results from 5.3.3 showed only a marginal satisfaction difference (1%-2%) between complete resource need prioritization versus complete relational prioritization in Laurelhurst and South Park neighborhoods.

The decentralized scheme is versatile across different rescue stages.

For communities with a social capital structure suitable for decentralized allocation, such as Laurelhurst and South Park, our analysis in 5.3.4 demonstrated that the decentralized approach consistently outperforms centralized methods in average household satisfaction under different rescue times, as resources are covered more quickly and extensively.

6. Discussion

The primary intention of this research is to propose a method for quantifying and assessing community social capital and to explore the potential for spontaneous mutual aid and peer-to-peer sharing among families driven by social capital during disasters. Our ultimate objective is to provide recommendations for community disaster response. Based on our findings, we put forth several policy and technological suggestions:

Community Disaster Response Recommendations:

In emergency disaster response, adopting a decentralized approach that leverages peer-to-peer sharing among residents could be beneficial. It is important to tailor the implementation of this decentralized resource distribution scheme to the community's population size to determine the optimal number of sharing captains. Additionally, an excessive focus on the sharing priorities of these captains is unnecessary. The community can encourage but does not need to demand that they act completely rationally and equally in sharing resources with people in the community. This is because prioritizing resource needs over social relationships at sharing captains results in only a marginal increase in overall community satisfaction. However, such a rational prioritization approach can be particularly challenging for individuals during disasters ([Perry Jr et al., 1983](#)).

Community Disaster Preparedness Recommendations:

(1) Enhance community social capital: The community's social capital situation is crucial for implementing decentralized resource distribution. Communities should organize regular team-building activities and provide platforms for residents to interact, fostering trust and a sense of belonging. Encouraging more residents to participate in public affairs and building more social connections can improve community cohesion and strengthen social networks ([Alesina and La Ferrara, 2002](#)). An example worth noting is the Laurelhurst Emergency Action Plan ([LEAP, 2022](#)), a volunteer organization dedicated to bringing people together through various training and preparedness courses, educating Laurelhurst residents about steps to take before, during, and after an earthquake.

(2) Focus on potential sharing captains: Identifying and appointing potential sharing captains in the community during the disaster preparedness phase is important. Our research indicates that a small segment of the community with a broader willingness to share plays a pivotal role in decentralized emergency resource distribution. These individuals are likely candidates for sharing captains. Therefore, community disaster preparedness should focus on their identification and training for orderly response in emergencies. For example, in the LEAP of Laurelhurst community, they divide the community into zones ([LEAP, 2023](#)) and assign a 'captain' to each zone, who can play a key role as a sharing captain in emergencies and coordinate resource distribution. However, the community does not need to put much effort into encouraging each individual to share with everybody in the community or to establish many more social relationships beyond their willingness, as these factors have limited enhancement on emergency resource distribution and are difficult to achieve.

(3) Develop strategies for different communities: Each community's social capital profile is unique, as evidenced by the disparity in social ties between Laurelhurst and South Park. Tailoring a disaster response process to communities' different 'personalities' is necessary. As mentioned in the Seattle Neighborhoods Actively Prepare ([EM, 2023](#)) program, there is no right or wrong in different community organization methods. The key lies in developing a customized plan and ensuring preparedness. Our decentralized resource distribution method provides an example that is theoretically feasible but requires further testing in actual implementation. A suggested implementation process includes: i) conducting surveys to gauge social capital, including sharing preferences and social ties, trust, participation, etc; ii) identifying sharing captains based on residents' situations and willingness, and establishing a community-specific post-disaster action roadmap; iii) conducting training and drills to improve and adjust the response plan continuously.

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