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Solidarity and Asymmetric Returns in Digital Philanthropy: Division of Labor and Capital Conversion in Weibo's Stray Dog Rescue Network

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Abstract: Stray dog rescue on social media involves both low-cost information dissemination and labor-intensive offline rescue work, yet little is known about how these forms of labor are organized within online networks. Drawing on Durkheim's theory of social solidarity and Bourdieu's theory of field and capital, this study analyzes 201 Weibo accounts engaged in stray dog rescue. A directed follower network was examined using social network analysis, exponential random graph modeling (ERGM), and hierarchical multiple regression. The network contained 6,499 directed ties and formed a single weakly connected component, while also exhibiting selective patterns of tie formation, local clustering, and unequal centrality. ERGM results indicate strong homophily based on role, capital type, organizational form, and geographic region. Accounts operating across regions, with longer tenure, larger follower bases, and more diversified rescue functions were more likely to form network ties. Regression analyses further show that audience engagement was driven primarily by follower base and influencer-derived capital rather than by labor-intensive offline rescue roles. The findings reveal the coexistence of mechanical and organic solidarity, as well as an asymmetric conversion of rescue labor into platform attention.

Keywords: digital philanthropy, stray dog rescue, social network analysis, ERGM, social solidarity

1. Introduction

Stray animal rescue occupies an ambiguous space at the intersection of urban governance, voluntary civic action, and platform-mediated communication. A stray dog's movement from being discovered to being rescued usually involves several interdependent stages: field intervention, medical care and shelter placement, adoption matching, and information diffusion. These stages require different resources. Field intervention and placement depend heavily on time, space, money, embodied risk, and practical knowledge, whereas diffusion depends more on platform visibility, audience size, and communication skills. Research on animal sheltering also shows that rescue systems involve behavior assessment, adoption placement, medical care, community cooperation, operational management, and cross-sector coordination, which are difficult for a single actor to accomplish alone (Horecka & Neal, 2022). More broadly, disaster-recovery research shows that social media can simultaneously support donation, information assistance, social cohesion, and emotional support (Ogie et al., 2022), while research on adoptable-pet posts cautions that platform engagement is shaped by content presentation and cannot be equated directly with adoption or rescue outcomes (Morrison et al., 2024).

Digital platforms lower the threshold for public participation in philanthropy, but they do not eliminate differences among actors. Existing research shows that nonprofit use of social media is not limited to one-way information release; it also includes community maintenance, mobilization, and advocacy (Guo & Saxton, 2014; Lovejoy & Saxton, 2012). Organizational capacity, governance, and external environments shape whether nonprofit organizations can use platform tools effectively (Nah & Saxton, 2013). In addition, social media adoption

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by nonprofit organizations is related to their interorganizational network portfolios, especially open networks, cross-sector partners, and geographically distant partners (Özman & Gossart, 2024).

The Weibo accounts involved in stray dog rescue therefore cannot be treated as homogeneous actors simply because they share the same issue. Some are public-welfare-native actors whose core identity is long-term rescue. Some are professional cross-over actors such as veterinarians, pet hospitals, or lost-pet service providers who bring professional knowledge and industry resources into the rescue field. Others are influencer cross-over actors, such as pet influencers or content creators, who participate mainly through submissions, reposts, or issue amplification. Their organizational status, offline backing, geographic scope, account tenure, verification status, and followers may influence not only whether they are followed by others, but also whether their offline labor can be converted into digital engagement.

Durkheim's The Division of Labor in Society distinguishes mechanical solidarity, which is based on similarity and collective consciousness, from organic solidarity, which is based on differentiation and interdependence produced by social division of labor (Durkheim, 1893/2000). This distinction provides a useful starting point for examining online rescue networks: are ties among rescue accounts produced mainly by shared identity, region, capital type, and organizational similarity, or by the complementarity of differentiated rescue roles? However, Durkheim's theory tends to read interdependence as a source of moral integration, whereas Bourdieu's theory of field and capital reminds us that relations among actors also involve unequal capital endowments, capital conversion, and symbolic power (Bourdieu, 1986, 1989). Visibility on platforms is not a natural reward for labor; it is systematically shaped by followers, verification, organizational reputation, and prior popularity.

This article takes directed following relations among Weibo stray dog rescue accounts as an observable digital relationship network. It treats rescue functions, organizational identity, capital type, geography, and platform resources as node attributes, and combines social network analysis (SNA), exponential random graph models (ERGM), and hierarchical multiple regression. The article asks how online rescue accounts are connected, which attributes shape tie formation, and whether offline rescue roles and organizational embedding can explain platform engagement beyond pre-existing visibility. By linking relationship formation with attention distribution, the study contributes to research on digital philanthropy, social solidarity, and the platformization of civic care.

2. Literature Review and Theoretical Framework

2.1. From mechanical to organic solidarity

For Durkheim, social solidarity is the central mechanism that sustains social order. In societies where division of labor is limited, members are connected because they resemble one another in lifestyle, belief, and value. As differentiation deepens, actors no longer unite primarily because they are similar; they become connected because they perform different functions and become mutually dependent (Durkheim, 1893/2000). Social division of labor is therefore not merely an economic arrangement that improves efficiency. It is also a mechanism for producing social relations.

Mechanical solidarity does not disappear from modern society. Even in differentiated societies, shared identity, local belonging, and common moral commitments remain powerful bases of connection. In online philanthropic networks, mechanical solidarity may appear as ties among accounts from the same region, accounts of the same organizational type, or accounts with similar capital types. Organic solidarity may appear as interdependence among field intervention, shelter placement, adoption matching, and information diffusion. Stray dog rescue is well suited to examine the coexistence of these mechanisms because its rescue chain requires both shared concern and differentiated labor. Chinese sociological discussions of Durkheim similarly emphasize that mechanical and organic solidarity may be empirically unified under deep division of labor, and that collective consciousness and resource exchange can coexist as sources of solidarity (Pan &

Li, 2013; Hu, 2023).

Studies of digital solidarity further suggest that online ties may take expressive forms, such as reposting, emotional support, and public statements, or more demanding forms that involve reciprocal obligations and offline action. Tewksbury (2018) shows that technologically embedded protest networks can connect digital belonging with analog mobilization. Research on solidarity in digital contexts also emphasizes that shared identity may motivate actors to support others and challenge existing arrangements (Subašić et al., 2008). Yet Durkheim also discussed abnormal forms of division of labor, including anomic and forced division, which means that differentiation does not automatically produce equal or stable integration. When the costs borne by different roles do not match the rewards they receive, division of labor may create new tensions. Recent work further distinguishes expressive digital solidarity from solidarity that entails reciprocal obligations and practical coordination (Kajta et al., 2025), and shows that digital technologies can re-mediate solidarity practices as information, labor, and participation are reorganized online (Stehrenberger & Schneider, 2023). These tensions also echo Chinese reinterpretations of Durkheim that stress the risks of anomie and disorder within organic solidarity (Lü, 2013), as well as research showing that solidarity in platformized labor settings is shaped by concrete labor organization rather than by shared values alone (Della Porta et al., 2022).

2.2. From functional interdependence to field position

Bourdieu's theory of field and capital helps explain inequality within relations of functional dependence. Social space is composed of differentiated positions occupied by actors with different volumes and structures of capital. Economic, cultural, social, and symbolic capital can determine positions in a field and can be converted into one another under specific conditions (Bourdieu, 1986). Social capital refers to actual or potential resources linked to durable networks of relations, whereas symbolic capital refers to recognized prestige, reputation, and legitimacy. This perspective transforms functional differences in the Durkheimian sense into positional differences within a field.

Bourdieu also emphasizes that power relations in a field are often naturalized through symbolic forms. In platform environments, high follower counts, verification marks, and high interaction metrics are easily interpreted as natural evidence of trustworthiness or influence. Yet these indicators are themselves outcomes of accumulated capital. The online network of stray dog rescue is therefore both a cooperative network and a field in which attention and legitimacy are continuously produced, recognized, and converted (Bourdieu, 1989).

This argument also justifies the use of digital relational data to study philanthropic fields. Oncini and Ciordia (2024), using Twitter following relations among charitable food provision organizations, argue that apparently weak digital ties may reveal mutual recognition, field boundaries, positional differences, and power asymmetries among organizations. Following relations cannot replace direct observation of collaboration, but they can show how actors publicly recognize one another, confirm similarity, and express relational proximity.

2.3. Networked organizations, digital philanthropy, and platform action

Organizational research has long treated networks as a form of coordination that differs from markets and hierarchies because it relies on reciprocity, reputation, and relational embeddedness (Powell, 1990). In interorganizational collaboration, the effectiveness of network governance depends on the number of participants, goal consensus, trust, and network-level administrative capacity (Provan & Kenis, 2008). Philanthropic action is especially network-dependent because individual actors rarely possess all necessary resources. They rely on networks to obtain information, volunteers, professional support, donations, and public recognition.

Social media has changed how nonprofit and philanthropic actors become networked. Lovejoy and Saxton (2012) classify nonprofit social media use into information, community, and action functions, showing that platforms are used not only to publish messages but also to maintain communities and mobilize participation. Guo and Saxton (2014) further show that social media is changing nonprofit advocacy, while Nah and Saxton (2013) demonstrate that adoption and use are shaped by organizational strategy, capacity, governance, and external conditions. Chinese studies similarly suggest that public-welfare organizations' social media use and effects are not uniform, but related to organizational attributes and resources (Wang et al., 2019). Digital transparency and accountability also matter for NGO participation and legitimacy (Baamonde-Silva et al., 2017). Chinese studies further show that social capital can strengthen organizational trust, shared values and self-organization can sustain collective action, online philanthropy often combines open group-based information flows with more bounded circle-based interaction, and grassroots organizations' online communication capacity is related to organizational scale and resource conditions (Zhang, 2013; Shen, 2017; Qiu, 2015; Ma et al., 2015).

Digital philanthropy has not made offline organization and local relations irrelevant. Platforms may help grassroots organizations cross territorial boundaries, raise funds, and mobilize publics, but online fundraising and communication remain shaped by legitimacy, institutional environment, and existing resource structures (Han et al., 2025; Zhou & Le Han, 2019). At the same time, social media operates through programmability, connectivity, popularity, and datafication, continuously turning followers, likes, reposts, and comments into visible ranking signals (van Dijck & Poell, 2013). Philanthropic actors may be able to speak, but whether they are heard depends on audience size, organizational resources, and platform logics (Guo & Saxton, 2018). Chinese research also suggests that internet-based charity is shaped by the relationship between official and civic organizations, because technology and institutions mutually select, constrain, and reconstruct one another (Liu, 2014, 2017). Trust in online philanthropy therefore depends on institutional organizations, new relational ties, and re-embedding mechanisms, while technological expansion may both erode and remake local forms of proximity (Zhao & Xu, 2019; Dong & Zhao, 2021). Studies of online charitable crowdfunding and public-welfare sharing further show that platform-specific relationships, user motivations, symbolic recognition, platform professionalism, and identity cues shape donation and sharing behavior (Zhong, 2015; Yin, 2018; Zhu et al., 2024).

2.4. Homophily and operationalization of node attributes

Social network research shows that homophily is a general mechanism of tie formation: actors with similar identities, statuses, or behavioral features are more likely to form relations (McPherson et al., 2001). In digital action networks, geographic proximity, language, and organizational identity may strengthen connection while also producing bounded information circles (Schröder & Pfeffer, 2025; Yang & Stoddart, 2021). In the Weibo stray dog rescue network, same-role, same-organization, same-capital, and same-region ties can therefore be read as empirical manifestations of mechanical solidarity or field-internal segmentation.

Based on the theoretical framework, this study groups node attributes into four categories. The first category is functional division of labor, including field intervention, shelter placement, adoption matching, and information diffusion. The second category is organizational and legitimacy attributes, including organizational status, offline institutional backing, and Weibo verification. The third category is spatial attributes, including geographic region and local or cross-regional scope. The fourth category is capital and platform-resource attributes, including capital type, account tenure, follower count, and repost, like, and comment engagement metrics. Table 1 summarizes the correspondence between variables and theoretical concepts.

Table 1. Operationalization of Node Attributes and Theoretical Concepts

Attribute variable	Operational meaning	Theoretical correspondence
Field intervention, shelter placement, adoption matching, information diffusion	Functional roles and labor costs in the rescue chain	Division of labor; organic solidarity
Role cluster	Information-diffusion dominant, intervention-linkage, full-process	Division-of-labor position; functional interdependence
capital type	Public-welfare-native, professional cross-over, influencer cross-over	Capital structure; capital conversion
Organizational status and offline backing	Organizational capacity and institutional legitimacy	Organizational capital; symbolic capital
Geographic region and spatial scope	Regional homophily and cross-regional action capacity	Mechanical solidarity; disembedding
Account tenure	Temporal accumulation and relationship sedimentation	Historical capital accumulation
Weibo verification	Visible platform-recognized identity marker	Symbolic capital
Followers	Accumulated visibility and potential audience	Digital social capital; influencer capital
Engagement	Platform attention and communication reward	Outcome of capital conversion

2.5. Research questions and hypotheses

The study integrates Durkheim, Bourdieu, and digital philanthropy research into a division-of-labor, embeddedness, and capital-conversion framework. Mechanical solidarity highlights similarity-based connection; therefore, accounts with the same role, organization type, capital type, or geographic region should be more likely to follow one another. Organic solidarity highlights interdependence generated by division of labor; therefore, accounts undertaking field intervention, placement, adoption matching, or cross-regional coordination may have higher relational value. Bourdieu's framework further suggests that capital structure will shape not only network embeddedness but also digital attention rewards.

The variable-entry order in hierarchical multiple regression follows this framework.

Model 1 first includes verification, account tenure, and followers to control platform visibility accumulated before or outside the rescue field. Model 2 adds spatial scope, role cluster, and organizational type to examine whether functional position and organizational embeddedness add explanatory power beyond platform capital. Model 3 finally adds capital type to test whether actors' entry capital further explains engagement. This order does not prove a causal chain; it compares the incremental explanatory power of theoretically meaningful variable blocks.

RQ1: What overall structure and node-position differences characterize the Weibo stray dog rescue account network?

RQ2: To what extent are following relations shaped by homophily, functional division of labor, organizational legitimacy, geographic embeddedness, and platform capital?

RQ3: Can rescue roles and organizational embeddedness explain engagement outcomes beyond existing platform visibility, and does capital type further shape attention distribution?

At the relationship-formation level, this study proposes:

H1: Accounts with the same role cluster are more likely to form following ties.

H2: Compared with information-diffusion-dominant accounts, intervention-linkage and full-process accounts have higher overall tie propensity.

H3: Accounts with the same capital type, organizational type, and geographic region are more likely to form ties.

H4: Institutionally backed accounts, cross-regional accounts, accounts with longer tenure, verified accounts, and accounts with larger follower bases have higher overall tie propensity.

At the engagement-reward level, the study proposes:

H5: Platform visibility capital significantly explains differences in engagement.

H6: Role division and organizational embeddedness significantly increase explanatory power beyond platform visibility.

H7: Capital type significantly increases explanatory power beyond platform visibility, role division, and organizational embeddedness, with influencer cross-over accounts receiving higher engagement than public-welfare-native accounts.

3. Research Design, Data, and Measurement

3.1. Sample discovery, inclusion, and network definition

The study examines Weibo accounts related to stray dog rescue. Data were collected from March 7 to April 29, 2026. The sample was constructed through purposive snowball expansion combined with manual screening. Starting from known stray dog rescue accounts, the researcher crawled their following lists and gradually discovered new candidate accounts along the observed following relations. Candidate accounts were then manually examined through their profile descriptions and visible historical posts. Accounts were included if they displayed continuous content related to stray dog rescue or explicitly identified themselves with rescue, sheltering, adoption matching, lost-dog searching, or relevant professional support. Search clues included Chinese keywords such as “stray dog rescue,” “adoption,” “shelter base,” “donation,” “rent,” and “food shortage.”

Accounts were excluded if they were obvious zombie accounts, inactive accounts no longer showing rescue activity, duplicates, or accounts with no substantive relation to stray dog rescue. Snowball expansion stopped when no new eligible accounts emerged along the collection paths. The final sample contained 201 accounts. The sample covers major relevant actors identifiable through the sampling paths but is not a complete census of all Weibo stray dog rescue accounts. It should therefore be understood as a purposive relational sample rather than a probability sample from which platform-wide proportions can be directly inferred.

Accounts are treated as nodes, and publicly visible directed following relations among them are treated as edges. Following relations usually change less frequently than single reposts, comments, or likes, and are therefore better suited for observing relatively stable relational cognition, sustained attention, and circle boundaries (Oncini & Ciordia, 2024). However, following is not equivalent to co-rescue, money flow, material support, or offline collaboration. The interpretation of network ties is limited to mutual recognition and willingness for relational proximity. The raw edge list contained 6,614 records, including 115 duplicate directed following records. Because following is a binary dyadic relation, the analysis uses 6,499 unique directed ties. Code auditing showed that the ERGM binary network statistics treated duplicate records as the same dyad; an explicit deduplication refit produced identical coefficients, standard errors, significance levels, AIC, BIC, and goodness-of-fit statistics.

3.2. Node attributes and coding rules

Node attributes were derived from two sources. The first was publicly visible Weibo account information, including registration year, verification status, follower count, repost, like, and comment engagement metrics, and institutional information in organizational certification or profile descriptions. The second consisted of manually coded attributes based on profiles and historical posts, including capital type, organizational status, offline backing, geographic region, spatial scope, and four rescue functions. Account tenure was calculated as 2026 minus the registration year. Follower count and repost, like, and comment engagement metrics were measured in units of ten thousand, with platform snapshot data ending on April 29, 2026. Account tenure and follower count were standardized by z-score before entering ERGM and regression models, while the dependent variable in regression remained raw engagement in ten-thousand units.

Capital type identifies the main resource base that an actor brings into the stray dog rescue field. Public-welfare-native accounts take stray dog rescue as their core identity and sustained content. Professional cross-over accounts are primarily pet hospitals, veterinarians, lost-pet service providers, or other professional actors who contribute expertise, medical capacity, or industry resources to rescue. Influencer cross-over accounts are pet influencers, content creators, or accounts with pre-existing audiences; they usually participate by accepting submissions, reposting lost-dog or rescue information, or amplifying the issue, without visible evidence of direct offline assistance. To protect individual rescuers, typical cases are described anonymously and account names are not used for moral evaluation.

Manual coding was rule-based but not automatic keyword assignment. Keywords were used as search prompts rather than final coding criteria. For example, terms such as “base,” “rent,” or “food shortage” were coded as shelter placement only when posts indicated that the account itself bore responsibility for sheltering, venue maintenance, or daily feeding. If all relevant posts were third-party reposts, the account was not coded as undertaking offline placement. Borderline cases were checked repeatedly through profile text, historical posts, and visible organizational evidence. Because the current study used single-coder rule-based coding, it reports transparent coding rules and acknowledges that future research should add independent double coding and intercoder reliability assessment (Lombard et al., 2002).

Table 2. Manual Coding Rules for Node Attributes

Variable	Main evidence for coding as 1 or category membership	Boundary or exclusion rule
Field intervention	The account itself records discovery, capture, emergency rescue, transfer, or medical transport.	Mere reposting of others’ rescue information is not coded as field intervention.
shelter placement	The account itself bears responsibility for a shelter base, foster placement, venue, rent, food shortage, or daily feeding.	Mentions of “base” without evidence of the account’s own placement responsibility are excluded.
Adoption matching	The account regularly posts adoption information with screening, home visits, agreements, transport, return visits, or matching procedures.	Occasional reposting of third-party adoption information without follow-up evidence is excluded.
Information diffusion	The account regularly posts or reposts rescue, lost-dog, fundraising, adoption, or help-seeking information.	Pet content unrelated to rescue is not coded as rescue information diffusion.
Organizational status	Profile, account name, or historical posts identify an organization, team, association, base, or platform identity.	Accounts acting only as individuals without stable collective identity are coded as 0.
Offline institutional backing	Observable civil-affairs registration, official NGO status, government or enterprise affiliation, authorization, or certified entity linkage.	Ordinary verification, personal reputation, or self-description as a team alone is not institutional backing.
Geographic region	Stable location is identified from profile, local identity, or verifiable IP/location information and coded by seven Chinese regions.	Unclear, purely online, or cross-regional accounts are coded as NA.
Spatial scope	Long-term coordination across multiple provinces or regions, or national online-platform activity, is coded as cross-regional.	Activities concentrated in one city/province are coded as local.
Weibo verification	A visible Weibo verification mark on April 29, 2026 is coded as 1.	This study only distinguishes verified and unverified accounts.

3.3. Clustering and Typology Construction

The four rescue-function indicators often co-occur within the same account. Using the four binary variables separately would make it difficult to summarize an account’s overall position in the rescue chain. This study used K-means cluster analysis implemented in SPSS based on Euclidean distance to classify accounts according to field intervention, shelter placement, adoption matching, and information diffusion. The number of clusters was theoretically specified as three; the maximum number of iterations was set to 10, and the algorithm converged at the third iteration. The three-cluster specification was theoretically motivated by the distinction among accounts mainly engaged in information diffusion, accounts engaged in intervention and linkage, and accounts close to a full rescue chain. Table 2 reports the unrounded cluster means to facilitate interpretation and avoid treating the resulting types as absolute categories, preventing the empirical types from being misread as absolute categories.

Organizational type was also constructed through SPSS Quick Cluster, using two binary variables: whether the account was organized and whether it had offline institutional backing. Three clusters were prespecified, the maximum number of iterations was 10, and convergence occurred at the second iteration. The three types correspond to theoretically meaningful combinations: institutionally backed actors, unbacked individuals, and unbacked organizations. The institutionally backed actor cluster displayed a mean score of 1.00 on institutional backing and 0.941 on organizational status, including 48 organizational accounts and three backed individual accounts; it is therefore named institutionally backed actors rather than backed organizations. These clustering procedures are used to build interpretable descriptive types. ANOVA significance in the SPSS output is not treated as proof that latent categories objectively exist.

Table 3. Role Cluster Centers and Cluster Sizes

Role cluster	Field intervention	shelter placement	Adoption matching	Information diffusion	n
Information-diffusion dominant	0.000	0.015	0.299	1.000	67
Intervention-linkage (semi-closed loop)	1.000	0.000	0.516	0.935	31
Full-process (all-round)	0.922	1.000	0.990	1.000	103

Table 4. Organizational Cluster Centers and Cluster Sizes

Organizational type	Organized	Offline institutional backing	n
institutionally backed actors	0.941	1.000	51
Individuals	0.000	0.000	27
Unbacked organizations	1.000	0.000	123

3.4. Descriptive statistics, analysis strategy, and ethics

Among the 201 accounts, 91.0% were public-welfare-native, 4.0% were professional cross-over, and 5.0% were influencer cross-over. Cross-regional accounts accounted for 19.4%, and verified accounts accounted for 56.2%. In terms of rescue functions, 62.7% had field-intervention records, 51.7% had physical-placement records, 68.7% had adoption-matching records, and 99.0% had information-diffusion records. East China was the largest geographic region, accounting for 24.4%. Thirty-nine accounts were coded as NA for geographic region because they were purely online influencer accounts or accounts whose offline work crossed multiple regions; all of them were coded as cross-regional in spatial scope. Follower count and engagement were highly right-skewed. Mean engagement was 2.0318 million, while the median was only 124,000; the maximum reached 74.847 million. This long-tail pattern is important for interpreting regression diagnostics.

Table 5. Descriptive Statistics of Continuous Variables

Continuous variable	N	Mean	SD	Median	Min	Max
Account tenure (years)	201	13.63	2.65	14.00	1.00	17.00
Followers (10,000s)	201	22.66	44.04	5.60	0.95	356.60
repost, like, and comment engagement metrics (10,000s)	201	203.18	872.50	12.40	0.36	7,484.70

The study proceeds in three steps. SNA describes overall connectivity, density, reciprocity, local clustering, community structure, and node-position differences. For the directed network, in-degree, out-degree, total degree, and directed betweenness centrality were calculated. Eigenvector centrality was used to identify nodes connected to other central nodes. K-core and Louvain community detection were performed after folding the network into an undirected binary network. ERGM was estimated in R with the network 1.20.0 and ergm 4.12.0 packages; all 201 nodes were successfully matched with the attribute table. In the model, nodematch terms test uniform homophily by role cluster, capital type, organizational type, and geographic region. Nodefactor and nodecov terms test effects of categorical and continuous attributes on overall incident tie propensity. Hierarchical multiple regression compares incremental explanatory power for engagement. Reference categories were unverified, local, information-diffusion-dominant, individual, and public-welfare-native. Model estimation and diagnostics follow the ERGM implementation discussed by Hunter et al. (2008).

All data came from publicly visible Weibo pages and are used only for academic research. The article does not display account names in the main text, tables, or figures; it does not morally evaluate individual rescuers and does not disclose personal information unrelated to the research questions. For individual rescuers and small teams, even publicly visible information is presented in aggregated form to reduce identifiability. Internet research ethics emphasizes that public availability does not remove the researcher's responsibility to consider context, potential harm, and anonymization (Franzke et al., 2020). The raw data containing account identifiers are therefore not released as a public appendix.

4. Results

4.1. SNA: Limited Ties, Overall Reachability, and Unequal Positions

After deduplication, the network contained 201 nodes and 6,499 unique directed following ties. With self-loops excluded, 40,200 possible directed ties existed, producing a density of 0.1617. The rescue accounts did not form a nearly complete network; most possible following relations were absent. The network thus retains clear relational selectivity.

Nevertheless, all 201 accounts belonged to a single weak component, and the largest strong component contained 193 accounts. This means that, when direction is ignored, all accounts enter the same relational system; even when direction is retained, most accounts can reach one another through directed paths. The undirected average shortest path length was 1.82 and the diameter was 4, indicating that most accounts are indirectly connected through a small number of steps. Reciprocity was 0.488, showing that bidirectional and unidirectional relations coexist. The undirected global clustering coefficient was 0.504, suggesting strong local cohesion among relational neighbors. These indicators together describe a network that is selective in direct ties but highly reachable and locally cohesive. The coexistence of reachability and local clustering also resonates with research on Weibo public-welfare information diffusion, which finds that communication resources tend to concentrate around a limited number of central nodes (Bian et al., 2022). It also echoes the Chinese distinction between open online "groups" and more bounded philanthropic "circles," where issue-based access and relationship-based clustering operate together (Qiu, 2015).

Node positions varied substantially. The mean in-degree and out-degree were both 32.33, and the mean total degree was 64.67. Yet the highest total degree was 195, about 3.02 times the mean; the maximum in-degree was 119 and the maximum out-degree was 145. Accounts with high in-degree are recognized and followed by others, whereas accounts with high out-degree display broader active following, information seeking, or resource searching. Out-degree centralization (0.563) exceeded in-degree centralization (0.433), suggesting that active outward connection was concentrated among a smaller number of actors.

The attributes of top central nodes reveal that network position is not identical to platform influencer. The top ten in-degree accounts were all public-welfare-native; six were full-process accounts, five were institutionally backed actors, and eight were verified. Their median follower count was 497,000 and their median engagement was 1.2515 million. The top ten eigenvector accounts were also all public-welfare-native, and eight were verified. By contrast, among the top ten out-degree accounts, six were full-process, six were unbacked organizations, and only three were verified. Their median follower count and engagement were 56,500 and 116,000, respectively. Being widely followed and actively following others are therefore different network positions: the former is closer to relational recognition, while the latter may reflect the need of rescue actors to search for information and maintain resource networks.

Betweenness centrality identifies bridge nodes located on many shortest paths. Among the top ten betweenness accounts, six were full-process, four were institutionally backed actors, eight were verified, and nine were public-welfare-native. Their median follower count and engagement were 655,000 and 1.264 million. These bridge positions tend to be occupied by accounts that combine rescue practice, organizational reputation, and platform visibility, although betweenness alone cannot prove actual cross-group collaboration.

Table 6. Main SNA Indicators

Indicator	Result	Structural implication
Nodes	201	Number of rescue-related accounts in the sample
Unique directed following ties	6,499	Binary ties after removing 115 duplicate records
Density	0.1617	Most potential ties were absent; ties were selective
Reciprocity	0.488	Bidirectional and unidirectional following coexisted
Largest weak component	201	All accounts entered one relational system
Largest strong component	193	Most accounts were mutually reachable through directed paths
Average shortest path (undirected)	1.820	Indirect distance among accounts was short
Diameter (undirected)	4	Even the farthest nodes were connected by few steps
Global clustering coefficient	0.504	The network showed local relational cohesion
Louvain communities	5	Several local groups were detected
Louvain modularity	0.144	Community boundaries existed but were not closed

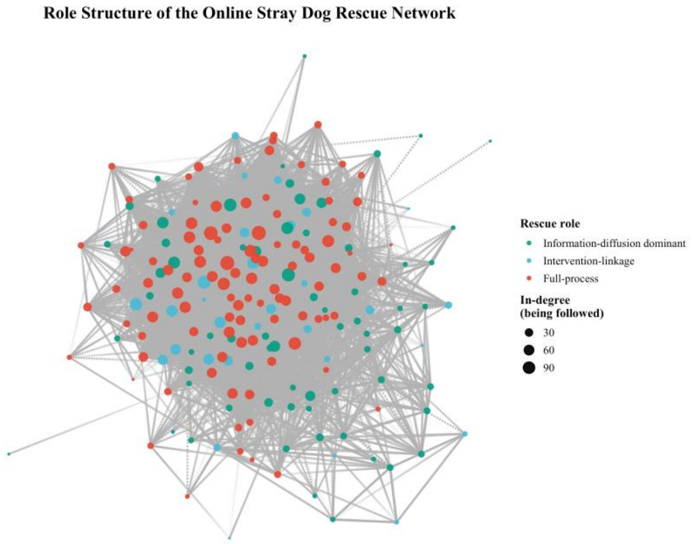

Figure 1. Role structure of the online stray dog rescue network. Node color represents rescue role, and node size represents in-degree, that is, the number of times an account was followed by other sampled accounts.

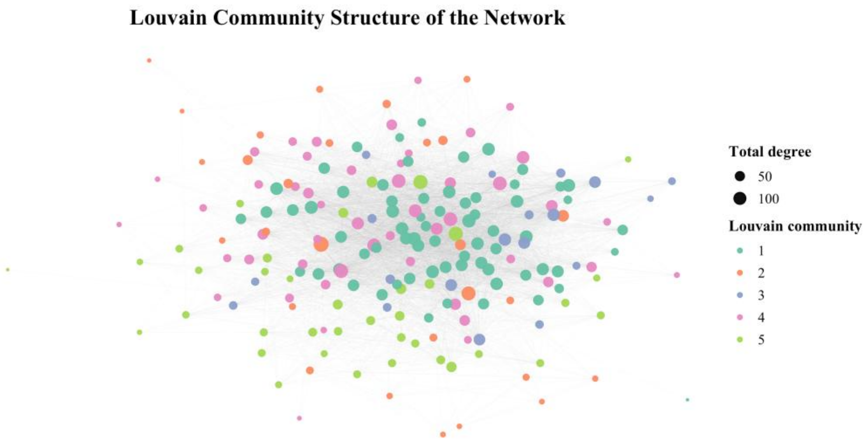

Figure 2. Louvain community structure of the online stray dog rescue network. Node color represents detected community, and node size represents total degree

4.2. ERGM: homophily, division of labor, and capitalized embeddedness

ERGM examines which factors increase the conditional probability of a following tie after controlling for other node attributes. Coefficients are on the log-odds scale; positive coefficients indicate increased tie propensity, while negative coefficients indicate decreased tie propensity. The edges coefficient was -4.013 ($p < .001$), corresponding to a baseline relationship probability of about 1.78% in the reference condition. This result is consistent with the limited density observed in SNA: without attribute matching or resource advantages, any two accounts have a low probability of forming a following tie.

The null deviance was 55,729 and the residual deviance was 32,062, a reduction of about 42.5%. AIC was 32,092 and BIC was 32,221. This deviance reduction indicates that node attributes add substantial explanatory information beyond the baseline tie probability. AIC and BIC, however, should be used mainly for comparison with alternative candidate models rather than as independent evidence of perfect fit.

First, the network displayed significant homophily consistent with mechanical solidarity. Accounts with the same role cluster were more likely to form ties ($\beta = 0.331$, $p < .001$), and accounts with the same organizational type also displayed significant homophily ($\beta = 0.252$, $p < .001$). Same geographic region had a positive effect ($\beta = 0.466$, $p < .001$), indicating that local embeddedness still matters in social media rescue networks. The strongest homophily effect came from capital type ($\beta = 1.534$, $p < .001$): the odds of a tie between accounts with the same capital type were about 4.64 times the odds between accounts with different capital types. This supports H1 and H3 and is consistent with general homophily theory (McPherson et al., 2001). The strength of capital-origin homophily suggests that the network is shaped not only by shared functions but also by field segmentation according to entry paths and resource bases.

Second, division-of-labor position shaped network embeddedness. Compared with information-diffusion-dominant accounts, intervention-linkage accounts had a significantly higher overall tie propensity ($\beta = 0.759$, $p < .001$), as did full-process accounts ($\beta = 0.270$, $p < .001$). H2 is therefore supported. Accounts undertaking field intervention, adoption matching, or multiple rescue stages were more likely to become part of the relational network. This finding matches the logic of organic solidarity: when accounts possess practical functions in the rescue chain, their relational value comes not only from shared concern but also from other actors' dependence on their functional resources. At the same time, same-role homophily remained significant, showing that similarity-based grouping and functional value operate together.

Third, capital and organizational legitimacy influenced network embeddedness. Relative to professional cross-over accounts, public-welfare-native and influencer cross-over accounts had higher overall tie propensity. Relative to institutionally backed actors, individual accounts and unbacked organizations had lower tie propensity. Account tenure and follower count also had positive effects. These findings suggest that long-term welfare identity, existing influencer, institutional backing, time accumulation, and platform visibility can all be converted into relational advantages. They support H4 for backing, tenure, and follower count, but the verification coefficient was significantly negative. Platform verification is an externally granted symbolic marker, yet relational recognition inside the rescue field may rely more on sustained participation, followers, or organizational reputation, a distinction consistent with institutional accounts of legitimacy (Suchman, 1995). Platform-granted symbolic status and field-internal relational capital are therefore not equivalent. This interpretation is also consistent with Chinese studies arguing that social capital enhances organizational trust and that online philanthropy requires institutionalized organizations and newly embedded relational ties to sustain trust (Zhang, 2013; Zhao & Xu, 2019).

Finally, cross-regional accounts had higher tie propensity than local accounts ($\beta = 0.302$, $p < .001$), while same-region homophily was also significant. Digital philanthropy thus exhibits a dual spatial logic. Actors still rely on local similarity to build trust and connection, but actors with cross-regional capacity can connect broader resources. Digital space does not replace locality; it layers cross-regional ties on top of local networks. This finding echoes studies showing that online networks remain geographically patterned (Takhteyev et al., 2012) and that distant partners can strengthen nonprofit digital adaptation (Özman & Gossart, 2024).

Table 7. ERGM Results

Term	Estimate	SE	z	p	OR
Edges	-4.013	0.183	-21.937	< .001	0.018
Same role cluster	0.331	0.033	10.004	< .001	1.392
Role cluster 2: Intervention-linkage	0.759	0.034	22.511	< .001	2.136
Role cluster 3: Full-process	0.270	0.027	9.978	< .001	1.310
Same capital type	1.534	0.125	12.272	< .001	4.637
Public-welfare-native	0.393	0.123	3.197	.001	1.481
influencer cross-over	0.328	0.115	2.860	.004	1.389
Weibo verification	-0.130	0.025	-5.121	< .001	0.878
Same organizational type	0.252	0.032	7.845	< .001	1.287
Organizational type 2: Individual	-0.417	0.039	-10.638	< .001	0.659
Organizational type 3: Unbacked organization	-0.508	0.028	-18.129	< .001	0.602
Same geographic region	0.466	0.036	13.083	< .001	1.594
Cross-regional scope	0.302	0.033	9.034	< .001	1.353
Account tenure (z)	0.324	0.013	24.674	< .001	1.383
Followers (z)	0.139	0.011	13.205	< .001	1.149

Note. MLE estimates are reported on the log-odds scale. OR = exp(Estimate). Reference categories for nodefactor terms are information-diffusion dominant, professional cross-over, and institutionally backed actors. Null deviance = 55,729; residual deviance = 32,062; AIC = 32,092; BIC = 32,221

Goodness-of-fit diagnostics simulated 100 networks from the model and compared in-degree, out-degree, dyadwise shared partners, and edgewise shared partners with the observed network. The degree distributions were partially reproduced, especially across most in-degree and out-degree ranges. However, shared-partner distributions showed deviations, implying that local closure and shared-partner structures are not fully captured by the current dyad-independent specification. The results should therefore be interpreted as evidence about attribute effects rather than as a complete structural model of all network dependence. This caution is consistent with comparative network research showing that reciprocity, transitivity, and skew vary across positive social networks and should not be assumed to be captured by a single attribute-based specification (McMillan et al., 2022).

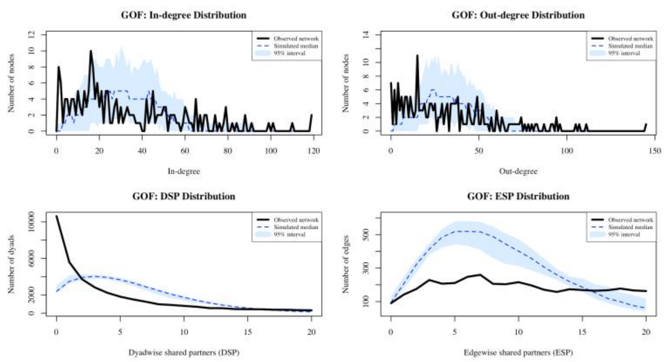

Figure 3. ERGM goodness-of-fit diagnostics. The black line represents the observed network, the dashed blue line represents the median of simulated networks, and the shaded area represents the 95% simulation interval.

4.3. Hierarchical multiple regression: capital bias in digital engagement outcomes

The study further used repost, like, and comment engagement metrics, measured in ten-thousand units, as the dependent variable in hierarchical multiple regression. This analysis is hierarchical multiple regression in the sense of theoretically ordered block entry; it is not a random-effects multilevel model. Model 1 includes verification, standardized account tenure, and standardized followers. Model 2 adds spatial scope, role cluster, and organizational type. Model 3 adds capital type.

Model 1 was significant, $F(3, 197) = 12.533$, $p < .001$, explaining 16.0% of the variance in engagement. H5 is supported. Followers had a significant positive effect ($\beta = 0.267$, $p < .001$), showing that existing audience size is an important basis of platform engagement. This is consistent with platform popularity logic and the argument that nonprofit actors must obtain attention to exert public influence (Guo & Saxton, 2018; van Dijck & Poell, 2013). Account tenure had a significant negative effect in Model 1 ($\beta = -0.240$, $p < .001$), and verification was not significant.

Model 2 increased R^2 to 0.227. The incremental explanatory power of the added variables was 0.067 and significant, $\Delta F(5, 192) = 3.341$, $p = .006$. H6 is supported at the block level. Cross-regional scope had a significant positive effect ($\beta = 0.221$, $p = .009$), suggesting that actions crossing local boundaries are more likely to attract platform attention. However, full-process and intervention-linkage accounts did not significantly differ from information-diffusion-dominant accounts, and organizational type did not reach conventional significance. Costly offline rescue work therefore does not automatically convert into more digital engagement. This finding also echoes Chinese studies showing that online public-welfare behavior and charitable information sharing depend on motivation, symbolic recognition, platform mechanisms, and user identification rather than on offline contribution alone (Zhong, 2015; Zhu et al., 2024).

Model 3 added capital type and increased R^2 to 0.540, with an adjusted R^2 of 0.516. The incremental explanatory power of capital type was 0.313, $\Delta F(2, 190) = 64.589$, $p < .001$, the largest increase among all variable blocks. H7 is supported. Relative to public-welfare-native accounts, influencer cross-over accounts received significantly higher engagement ($\beta = 0.691$, $p < .001$), and this standardized coefficient was much larger than those of other variables. Professional cross-over accounts did not significantly differ from public-welfare-native accounts. From Bourdieu's perspective, different forms of capital are not automatically equivalent. In a digital field where visibility and engagement are major rewards, influencer capital is much easier to convert than rescue experience or professional knowledge.

The regression results reveal an important gap between relational embeddedness and attention reward. ERGM showed that tenure, cross-regional action, complex rescue roles, and organizational backing increase tie propensity. In the engagement model, however, role clusters were not significant, tenure and cross-regional effects disappeared after capital type entered, and influencer cross-over identity plus followers dominated. Being able to connect with others and being able to obtain engagement are therefore not the same. Accounts that perform costly physical labor may have relational value without receiving digital visibility proportional to their labor, while actors with pre-existing influencer can more easily convert external capital into platform rewards.

Model diagnostics showed no severe multicollinearity or residual autocorrelation. The maximum VIF in the final model was 2.912, the maximum condition index was 9.476, and the Durbin-Watson statistic was 1.941. Yet engagement was highly skewed (skewness = 6.564), and standardized residuals ranged from -4.093 to 6.842, indicating possible influence from long-tail distribution and extreme cases. Since all accounts are also embedded in one relational network, ordinary least squares assumptions of distribution, homoscedasticity, and independent observations may be challenged. The regression results should therefore be read as conditional associations rather than strict causal effects.

Table 8. Hierarchical Multiple Regression Predicting Engagement

Variable	Model 1 β	Model 2 β	Model 3 β
Verification	0.106	0.126	0.048
Account tenure (z)	-0.240***	-0.157*	0.001
Followers (z)	0.267***	0.199**	0.227***
Cross-regional scope		0.221**	0.031
Full-process		0.047	0.021
Intervention-linkage		-0.054	-0.006
institutionally backed actors		-0.169	0.140
Unbacked organizations		-0.036	0.242**
influencer cross-over			0.691***
Professional cross-over			-0.053
R^2	0.160	0.227	0.540
Adjusted R^2	0.147	0.195	0.516
ΔR^2	0.160***	0.067**	0.313***

*Note. Reference categories are unverified, local, information-diffusion dominant, individual, and public-welfare-native. *** p < .001, ** p < .01, * p < .05.*

Table 9. Regression Diagnostics

Diagnostic	Result	Interpretation
Valid sample size	201	No missing cases after listwise deletion
Durbin-Watson statistic	1.941	No obvious residual autocorrelation
Maximum VIF in final model	2.912	No severe multicollinearity
Maximum condition index	9.476	Below common severe-collinearity warning level
Engagement skewness	6.564	Dependent variable was strongly right-skewed
Standardized residual range	-4.093 to 6.842	Potential extreme or high-influence cases exist

5. Discussion: Dual Solidarity and Asymmetric Rewards in Digital Philanthropy

Stray dog rescue is sociologically important not merely because it forms an observable digital philanthropic network, but because it shows how contemporary society responds to vulnerable life. Unlike fields with clear institutional responsibility, stray animal rescue often operates under insufficient institutional provision and blurred responsibility boundaries. Much rescue work is voluntarily undertaken by civic actors. In this context, Weibo is not only a space for information diffusion; it is also an infrastructure through which actors coordinate resources, organize action, and express care for vulnerable life.

Combining SNA, ERGM, and hierarchical regression reveals three layers in the Weibo stray dog rescue network. The first layer is overall connectivity generated by a shared issue. All accounts entered the same weak component, meaning that stray dog rescue has become a recognizable relational space on Weibo. The second layer is selective tie formation through homophily and functional dependence. Accounts connect by region, organizational type, role type, and capital type, while accounts with complex rescue functions, cross-regional scope, and longer accumulation are more embedded in the network. The third layer is capital bias in engagement outcomes. Platform attention is not distributed according to the complexity or cost of rescue labor; it is strongly shaped by follower base and influencer cross-over identity.

These findings show that mechanical and organic solidarity coexist in digital philanthropy. Shared region, similar organizational identity, and common capital type provide bases for mechanical solidarity. Role division and cross-regional coordination reflect organic interdependence within the rescue chain. However, Bourdieu's perspective reveals that organic solidarity does not imply equal resource distribution. Capital carried into the field differs across actors, and the convertibility of capital also differs. Influencer capital converts into engagement more easily than costly offline rescue labor. This generates an asymmetry between relational need and attention reward.

The study therefore cautions against two simplified descriptions of online rescue networks. They are not merely loose emotional communities built on compassion, because the network shows role specialization, organizational embedding, bridge positions, and cross-regional relations. They are also not ideal cooperative networks governed only by functional complementarity, because capital type and platform popularity strongly shape which actors become visible. The Weibo stray dog rescue network is better understood as a digital philanthropic field structured by common values, local relations, functional division of labor, and platform capital. Solidarity sustains rescue action, while capital differences determine who is seen, followed, and rewarded with engagement.

Table 10. Summary of Hypothesis Tests

Hypothesis	Result	Main basis
H1 Same role clusters are more likely to form ties	Supported	Role-cluster homophily was significantly positive
H2 Intervention-linkage and full-process accounts have higher tie propensity	Supported	Both nodefactor coefficients were significantly positive
H3 Same capital type, organization type, and region increase ties	Supported	All three nodematch coefficients were significantly positive
H4 Backing, cross-region, tenure, verification, and followers increase tie propensity	Partly supported	Backing, cross-region, tenure, and followers matched expectations; verification was negative
H5 Platform visibility capital explains engagement	Supported	Model 1 R^2 and follower effect were significant
H6 Role and organizational embeddedness add explanatory power	Supported at block level	Model 2 ΔR^2 was significant, although role variables were not
H7 Capital type adds explanatory power; influencer cross-over earns more engagement	Supported	Model 3 ΔR^2 and influencer cross-over coefficient were significant

6. Conclusion, Limitations, and Future Research

This article examined 201 Weibo stray dog rescue accounts through SNA, ERGM, and hierarchical multiple regression. The network had limited density but high reachability: all accounts entered one weak component, the largest strong component contained 193 accounts, and local clustering was substantial. ERGM results demonstrated significant homophily by role cluster, capital type, organizational type, and geographic region, as well as positive tie-propensity effects for complex rescue roles, cross-regional scope, account tenure, and follower count. Regression results showed that engagement was explained most strongly by followers and influencer cross-over identity, not by costly offline rescue roles. The

central theoretical finding is that digital philanthropy combines mechanical solidarity, organic solidarity, and unequal capital conversion. The rescue network is sustained by shared concern and functional interdependence, but platform attention is allocated asymmetrically.

Several limitations should be noted. First, the sample is limited to Weibo and cannot be generalized directly to WeChat, Douyin, Xiaohongshu, offline rescue networks, or other countries. Second, following relations capture stable relational cognition and public proximity but cannot directly measure actual collaboration, joint rescue events, money flows, material flows, or offline outcomes. Future studies could combine following data with reposts, @ interactions, shared rescue events, donation records, interviews, or ethnographic observation. Third, capital type is an analytical classification constructed for this study; it has strong explanatory power here but should be applied cautiously in other fields. Fourth, manual coding was conducted through transparent rules and repeated checks, but independent double coding and intercoder reliability should be added in future work. Finally, the engagement outcome is long-tailed and platform-specific; additional robustness checks using log-transformed engagement, robust regression, or network-autocorrelation models would strengthen causal interpretation.

Despite these limitations, the study offers a relational approach to digital philanthropy that connects network formation with attention distribution. It shows that online care for vulnerable life is organized through both solidarity and inequality: shared moral concern makes the network possible, division of labor makes rescue action workable, and capital conversion determines whose labor becomes publicly visible.

Conflict of Interest

The authors declare that they have no conflicts of interest to this work.

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