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From stakeholder mapping to statistical modeling: an illustrative demonstration of end-to-end Net-Map methodology for health governance analysis

Bianca-Elena Mihăilă^{1,2*}, Marian-Gabriel Hâncean^{1,2}, Marius Geantă², Cosmina Cioroboiu², Jürgen Lerner³, José Luis Molina⁴, Antonin Tron-Lozai^{1,2}, Bogdan-Adrian Vidraşcu^{1,2} and Iulian Oană^{1,2}

Abstract

Background Coordinating primary cancer prevention in Europe requires alignment across the EU, national, and local actors. Yet governance relations are challenging to observe. We used a participatory network approach to make relationships visible and test which ties are associated with funding. This study serves as a methodological demonstration to illustrate the complete Net-Map research cycle from data collection to statistical analysis.

Methods Three Net-Map sessions (January–February 2024) with a national NGO expert panel elicited stakeholders and ties for authority, influence, and funding, followed by validation. Canvases were used to record the information, and they were digitized afterwards into edge and attribute files. We described network structure and estimated four nested exponential random graph models (ERGMs) for the directed funding network, progressively adding governance level (EU, national, local), formal authority, and informal influence as predictors of tie formation. Model diagnostics included goodness-of-fit assessment, structural extensions controlling for degree heterogeneity and clustering, and robustness checks across network subsets.

Results The final network comprises 128 organizations and 836 funding ties (density 5.14%). Funding is predominantly cross-level (71.4%). EU actors show the strongest outward activity (EU-national density 17.8%; EU-local 16.1%), while national-local is lower (6.2%). In ERGMs, influence is the strongest correlate of funding (OR 168.54, $p < 0.001$), authority is positive but smaller (OR 5.76, $p < 0.001$), and same-level funding is less likely (OR 0.35, $p < 0.001$). Model comparisons favored the full specification. Goodness-of-fit diagnostics were adequate for the modeled dyadic statistics. Supplementary structural extensions controlling for degree heterogeneity and clustering attenuate the influence OR to 41.49, while the authority OR remains stable (5.76–6.46), confirming that both effects are robust to model specification.

Conclusions This illustrative analysis claims that participatory Net-Map workshops, combined with formal network analysis are helpful in diagnosing coordination patterns in decentralized health systems. The findings

*Correspondence:
Bianca-Elena Mihăilă
bianca.mihaila@sas.unibuc.ro

Full list of author information is available at the end of the article



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suggest that authority and influence serve complementary functions in governance, with implications that warrant further investigation with broader panels and longitudinal designs. The results primarily serve as an example of methodological application rather than providing generalizable insights about Romanian cancer prevention governance.

Keywords Net-Map methodology, Stakeholder mapping, Primary cancer prevention, Public health policy, Social network analysis

Text box 1. Contributions to literature

- Demonstrates how participatory stakeholder mapping can be used to empirically describe governance structures and cross-level connections in population-level cancer prevention.
- Shows how qualitative, participatory mapping data can be systematically translated into reproducible network datasets and analyzed using statistical network models, illustrating a complete workflow from data collection to model-based inference.
- Provides a methodological illustration of how the organization and coordination of primary cancer prevention beyond clinical care, through multi-level governance arrangements, can be made empirically visible and statistically analyzed.
- Offers a transferable methodological approach for policy monitoring and system diagnosis in decentralized public health systems.

Background

Net-Map was developed as a participatory way to visualize stakeholder networks and power relations [1, 2]. Particularly, it combines stakeholder engagement with social network analysis (SNA) to generate structured, analyzable data. Applications span food systems, child nutrition, reproductive health, obesity prevention, and natural resource governance [3–7]. These studies show their value for mapping influence, authority, and resource flows in complex settings. Recent work argues for using Net-Map to integrate relational evidence into policy analysis [8, 9].

Despite its promise, several gaps remain in the literature. First, most applications have been in the *Global South* (e.g., Ghana, Nigeria, Ecuador, Nepal), while European health governance has received little attention [3, 7, 10–12]. Second, few studies have applied Net-Map across the full research cycle: while the participatory phase is well developed, systematic integration with advanced statistical analysis remains rare, limiting its contribution to policy and systems research.

Cancer provides a compelling test case for addressing these gaps. Globally, there were 19.3 million new cancer cases in 2020, with projections of 28.4 million annually by 2040 [13]. Europe, home to less than 10% of the world's population, carries 25% of this burden [14]. In the European Union (EU), incidence and mortality continue to rise [15], with particularly high rates in Eastern Europe. In Romania, cancer is the second leading cause of death, responsible for 19% of all deaths in 2022 [16, 17].

Between 30% and 50% of cancer cases are considered preventable [18]. The European Commission [19] and the World Health Organization [20] highlight primary prevention strategies, including reducing tobacco and alcohol use, promoting healthier diets and physical activity, vaccination, and mitigating environmental risks. Implementing these strategies requires coherent governance frameworks that extend beyond biomedical interventions to address structural determinants of health. Yet, responsibilities for prevention are distributed across local, national, and supranational actors, including ministries, regulatory agencies, professional associations, civil society, patient groups, and EU institutions. This complexity often produces fragmented strategies, weak coordination, and inequitable allocation of resources. Similar challenges have been documented in primary healthcare systems more broadly, where stakeholder-informed analyses reveal governance dynamics not captured by formal documentation alone [21]. Consequently, this makes cancer prevention governance a vital framework for understanding how decentralized health systems operate.

This governance complexity connects to two theoretical traditions. Multilevel governance (MLG) theory distinguishes between Type I arrangements (nested, non-overlapping jurisdictions) and Type II arrangements (task-specific, overlapping, flexible configurations that cut across jurisdictional boundaries) [22]. Cancer prevention governance exhibits Type II characteristics: responsibilities are distributed across EU, national, and local levels; involve actors from multiple sectors; and are organized around specific tasks rather than following a single hierarchical chain. Network governance theory further suggests that coordination in such inter-organizational settings depends on both formal institutional channels and informal relational mechanisms, and that these may serve complementary rather than substitutive functions [23]. In health systems specifically, decentralization creates coordination challenges that formal mandates alone do not resolve [24–25]. Both traditions imply that governance relationships (particularly informal ones) need to be empirically observed, but neither offers well-developed tools for collecting structured relational data at the inter-organizational level. This is the gap that participatory network data collection approaches like Net-Map [1, 26] address.

Analyzing such governance processes through social network analysis requires structured relational data (e.g., directed ties between identified actors) as input. Several data collection strategies exist. Survey-based instruments are standard but require a predefined actor boundary and individual respondents with visibility across the network [27, 28]. Document-based coding captures formally recorded relationships but misses informal influence. Stakeholder analysis identifies actors and their attributes but does not typically elicit directed inter-organizational ties [29], while participatory systems mapping captures causal mechanisms at the variable level rather than between organizations [30]. When governance relationships are complex, multiplex, and undocumented (as in cancer prevention, where no stakeholder registry exists and informal influence does not appear in administrative records), a data collection approach is needed that can simultaneously generate the actor boundary and elicit multiple directed tie types in a structured format amenable to network modeling. Net-Map [1, 26] is a participatory data collection tool designed for this purpose: it produces directed edge lists with multiple tie types and actor attributes through facilitated expert elicitation. Its protocol has been applied across food systems, natural resource governance, and health policy [3–7], but it remains underutilized in European health systems and has not previously been applied to cancer prevention governance [31].

Our study addresses these gaps by applying Net-Map to primary cancer prevention governance in Romania, with a focus on stakeholders involved in implementing the European Code Against Cancer [20, 32]. Building on recent research into social determinants and prevention [33–35], we combine participatory mapping with advanced social network analysis (exponential random graph models) to examine how influence and authority ties are associated with directed funding across governance levels (EU, national, local). We contribute to health policy and systems research in three ways: (1) we offer one of the few European applications of participatory network mapping in public health, (2) we extend Net-Map across the full research cycle (from stakeholder elicitation and consensus validation to reproducible, model-based analysis), and (3) we show how multi-level structures and informal influence relate to the distribution of prevention resources, generating transferable, system-diagnostic insights for strengthening collaborative governance in decentralized health systems. Together, these contributions position Net-Map not only as a methodological innovation but also as a diagnostic tool for informing prevention policy and guiding more equitable allocation decisions in complex systems. This cross-sectional study design followed the Strobe Statement (see Additional file 1).

Methods

Exercise design and facilitation

Net-Map is a participatory interview-based mapping method that integrates *social network analysis* with *influence mapping* to visualize stakeholder relationships and perceived power dynamics [1]. In this study, we applied Net-Map to analyze the multi-layered governance of primary cancer prevention in Romania, with a particular focus on stakeholders involved in implementing the *European Code Against Cancer* (ECAC) [20].

The choice of Net-Map was motivated by two considerations. First, Romania's health system context: while cancer is the country's second leading cause of death, the absence of a national cancer registry has led to fragmented data on incidence, outcomes, and survival. In this environment, prevention is crucial, yet it requires coordinated action across a fragmented governance landscape. Lessons from the *Karelia Project* on cardiovascular prevention argued that prevention strategies are more effective when supported by collaborative networks [36, 37]. Second, the data collection rationale: cancer prevention governance involves actors from multiple sectors (e.g., tobacco regulation, food policy, vaccination, and environmental health) at multiple administrative levels, connected through relationship types that are largely undocumented. Net-Map addresses this data collection challenge through three design features. The mapping canvas is spatially organized by governance level, making cross-level ties an explicit focus of elicitation. Multiple tie types (authority, influence, funding) are elicited simultaneously over the same actor set, producing the multiplex relational data that our SNA models require. And the group format allows participants with complementary expertise to jointly construct the network, providing cross-level visibility that no single informant would have. We split the exercise across sessions (within-level ties first, cross-level ties second) to ensure that mapping across administrative boundaries received dedicated attention. The methodological choices prioritized demonstrating the complete Net-Map-SNA workflow (from participatory data collection to model-based inference) over maximizing representativeness. This analysis serves as an illustrative case study to show researchers how to implement the full research cycle.

The Net-Map exercise was conducted through three in-person sessions (January–February 2024) in Bucharest, Romania. Each session lasted approximately five hours. Splitting the exercise into multiple meetings minimized participant fatigue and allowed for reflection between stages. Namely, eliciting stakeholders and detecting their relationships are cognitively demanding tasks for participants [38, 39].

Session 1 (January 20, 2024) consisted of identifying relevant actors and mapping within-level relationships

(i.e., relationships among organizations of the same level). Session 2 (January 26, 2024) focused on the mapping of cross-level relationships (EU, national, and local). Session 3 (February 2, 2024) addressed the validation of the network maps. All three sessions were facilitated by a lead sociologist with extensive experience in qualitative sociology, supported by two assistants. Consistent with Net-Map principles, facilitators ensured clarity in problem framing, guided discussions, and moderated dynamics to avoid dominance by individual participants. All sessions were video-recorded to capture participant reasoning and support coding.

Participants and setting

We purposively recruited five experts from the same non-profit organization (NGO), a national organization with longstanding, multi-level engagement in primary cancer prevention (local implementation partnerships, national policy dialogue, and interfaces with European initiatives). This embedded, practice-based panel, was selected for three reasons. First, the NGO maintains continuous operational links across levels and sectors, providing participants with comprehensive visibility into stakeholders and inter-organizational ties relevant to the ECAC. Second, shared technical language and institutional memory facilitated the efficient and high-fidelity elicitation of complex networks within the time and cognitive constraints of Net-Map. Third, panel members covered complementary functional roles (policy design/regulation, financing/commissioning, implementation/coordination, data analysis and reporting), ensuring breadth of perspectives despite a single organizational home. Eligibility required ≥ 10 years of experience in public health/health policy, direct involvement in primary prevention and/or ECAC related activities, and routine collaboration with actors at local, national, and European levels. We did not aim for statistical representativeness; the goal was to provide credible coverage of system-critical perspectives, thereby generating and validating the stakeholder map.

We recognized the risk of shared-organization bias (common frames or blind spots). To address this, we employed a scripted facilitation protocol with turn-taking and probe questions, conducted in three sessions to facilitate reflection and correction, required explicit consensus on actors and ties, and performed structured digitization and cross-checks of the map. We also triangulated the elicited actor list against public policy documents (e.g., national cancer plans, ECAC guidance, and documented disagreements and their resolution).

We note that Net-Map can be implemented with individual key informants or small groups. We chose a small-group format to enable triangulation and consensus-building while managing cognitive load. Larger

panels should be intentionally avoided: they have an increased risk of proving logistically and cognitively unwieldy (crowded canvases, slower facilitation, harder consensus, higher coding error), which jeopardizes data quality.

Using a single-NGO panel may over-represent organizational perspectives. We address this by transparently reporting recruitment, providing open materials/code, and emphasizing that findings are diagnostic and meant to inform further multi-stakeholder validation rather than to claim population representativeness. Concerning the expert panel, there were no conflicts of interest. Additionally, the experts did not receive any honoraria for their study participation.

In total, twelve individuals were present at the sessions: five expert participants, one lead facilitator, two assistant facilitators, and four student observers responsible for logistics. To minimize potential bias, all experts were consulted equally during the mapping. Problem framing followed a standardized script derived from Schiffer [1] to ensure consistency. We conducted the sessions in Romanian (including the mapping). The dataset is translated into English. Three guiding questions structured the mapping: (1) *Who are the actors responsible for implementing the European Code Against Cancer in Romania?* (2) *What relationships connect them* (i.e., financial flows, influence, authority)? (3) *What are their primary motivations or roles in relation to cancer prevention?* Stakeholders were classified into four categories: *government (public)*, *private*, *academia*, and *civil society* [38–40]. Actors were also categorized by governance level: *local* (Argeş county), *national* (Romania), and *European* (European Union).

This study is designed as a methodological illustration. The choice of a single-NGO panel, while providing operational advantages for demonstrating the Net-Map process, necessarily limits the generalizability of findings. The results should be understood primarily as showing how the methodology works rather than providing comprehensive insights into the Romanian healthcare system.

Ethics

All research procedures complied with the Declaration of Helsinki and the European General Data Protection Regulation (GDPR). The study protocol was approved by the Ethics Committee of the Center for Innovation in Medicine (EC-INOMED Decision No. D001/09-06-2023 and No. D001/19-01-2024). Written informed consent was obtained from all participants. We anonymized personal identifying information after each interview and securely stored data on encrypted drives accessible only to authorized personnel.

Materials and mapping procedure

Mapping was carried out using large sheets of paper, post-it notes (for stakeholder names), and colored markers (for relational ties). Stakeholders were written on post-its, attached to the canvas, and linked according to three types of relationships. Namely, *authority*, i.e., formal power or decision-making capacity (policy enforcement, regulation, command); *influence*, i.e., ability to shape others' decisions or actions through expertise, advocacy, or strategic positioning; *financial resources*, i.e., transfer of funding or economic support.

In other Net-Map studies, the number of nominated stakeholders varied from 38 [41] to 83 [6]. In our case, we did not limit the experts in nominating stakeholders. Without a cap in the stakeholder elicitation process, the final map included 128 actors across governance levels. Parts of the original canvas are presented in Fig. 1.

Data structuring and preparation

The hand-drawn maps (the stakeholders and their relationships) were digitized into two datasets. An *edge list* file included source and target actors with relational type (financial flow, influence, authority), binary coded (1 = tie present, 0 = absent). An *attribute* file consisted of actor ID, name, organizational category (coded as: public, private, non-profit, and academia), and governance level (local, national, and European).

Digitization was conducted in two different working sessions. Student assistants entered the data into Excel, followed by cross-checking against the original maps. Experts validated the digital dataset in the third meeting. The dataset was then imported into RStudio (2023.06.1),

where we made use of various packages for the analysis (e.g., *igraph*, *statnet*, *ergm*).

Reliability and validation

We used a two-step reliability procedure. First, a *consensus mapping*. During elicitation, participants jointly discussed stakeholder inclusion and ties. Ties were recorded only when all participants reached explicit consensus. Disagreements were resolved through targeted prompts and, where applicable, by consulting official documents (e.g., legal mandates, program guidelines). Items without consensus were flagged and revisited in the validation session. Only ties with full agreement were retained in the final dataset.

Second, *double data entry and adjudication*. We implemented double data entry and adjudication: hand-drawn maps were independently digitized by pairs of observing student assistants, and discrepancies were reconciled by returning to the original canvases, session notes, and video; when ambiguity persisted, we consulted the expert panel. We did not compute a formal inter-coder agreement statistic during digitization because the task was a transcription of consensus-based, binary ties using pre-specified definitions. We acknowledge this as a potential limitation and recommend that future studies complement consensus and double-entry checks with blind recoding and κ/α estimates on a random subset. Based on our experience, limiting the number of stakeholders and tie types per session helps contain cognitive load and transcription errors.

While Net-Map is stakeholder-driven, facilitator influence is inherent [42]. To reduce bias, we: (i) used a standardized script and predefined guiding questions, (ii) moderated dominant participants while encouraging quieter voices, (iii) validated all actors and ties across three sessions, and (iv) required participant consensus before finalizing the maps. Observers (students) remained passive and uninvolved in discussions.

Inter-session reflection and blind-spot identification

The multi-session structure served an explicit bias-identification function. Between Sessions 1 and 2, the facilitation team reviewed video recordings and session notes to flag potential gaps in actor coverage and ambiguous tie classifications. Session 2 opened with a structured walk-through of Session 1 outputs, during which the panel was prompted to revisit, confirm, or revise previously mapped actors and within-level ties before proceeding to cross-level mapping. Between Sessions 2 and 3, the research team digitized the hand-drawn maps and compared the resulting actor list against public policy documents (national cancer plans, ECAC guidance, published program listings) to identify stakeholders or relationships that the panel may have omitted. Session

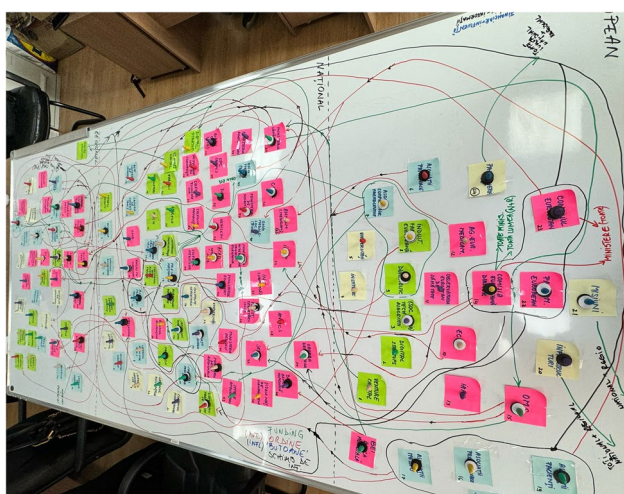


Fig. 1 An illustration of the multi-level stakeholder network elicited by the Net-Map exercise experts. Post-it colors mark the type of stakeholders (private, public, non-profit, and academic). Colored lines define the type of relationships connecting the stakeholders (funding, influence, authority). The canvas is split into three to delineate the stakeholders' levels (local, national, and EU)

3 was dedicated to validation: the digitized network was presented to the expert panel, and facilitators systematically reviewed flagged items (including actors appearing in policy documents but absent from the map and ties where digitization had revealed ambiguity). This structured inter-session protocol ensured that potential blind spots were surfaced incrementally rather than remaining unchecked through the entire exercise.

Statistical analysis

Prior to modeling, we calculated standard network descriptive statistics, including *density* (ratio of observed and theoretically possible ties) and cross-level tie patterns for each relationship type (authority, influence, financial flows). We examined the overlap between different relationship types to understand how formal and informal mechanisms relate to resource allocation patterns. We specifically analyzed cross-level coordination patterns by calculating the proportion of ties occurring within governance levels versus across levels (EU-national, EU-local, national-local) for each relationship type. Given the directed nature of funding relationships, we examined hierarchical resource distribution patterns by analyzing funding flows in both directions between governance levels (upward vs. downward funding).

We used Exponential Random Graph Models (ERGMs) [43] to examine which relational mechanisms are associated with the presence of a directed funding tie between

organizations (*i* funds *j*). ERGMs treat the observed network as one realization from a reference distribution in which the log-odds of a tie depend on a set of network statistics capturing baseline tie propensity (the tendency of tie formation within the observed network), homophily (the tendency of same-level organizations to share a tie), and dyadic covariates (influence and authority ties). This approach accounts for the interdependence of ties, an inherent feature of social and governance networks, and yields coefficients interpretable as log-odds (reported alongside odds ratios). The dependent variable was the binary directed funding network derived from the Net-Map sessions. All nodes appearing on the map were retained; multiple mentions were reconciled during digitization and validation. Self-ties were not permitted.

We estimated four nested ERGM specifications to assess the relative importance of different predictors: (1) baseline model containing only network density (*edges*), (2) adding governance level homophily effects (*same governance level*), (3) incorporating formal authority relationships, and (4) full model including informal influence relationships alongside all previous predictors. Table 1 briefly introduces the model terms.

Models were estimated using maximum pseudolikelihood (MPLE) as implemented in the *ergm* package. For interpretability, we present log-odds coefficients with standard errors (SE) and odds ratios (OR). We compared the full specification against nested models that omit each dyadic predictor in turn to assess incremental contribution using AIC/BIC comparisons. We evaluated (i) numerical convergence and parameter stability (including seed sensitivity) and (ii) Goodness of Fit (GOF) via simulated vs. observed distributions of in-degree, out-degree, edgewise shared partners, and geodesic distances (200 simulated networks). To assess whether network sparsity and degree heterogeneity inflate covariate estimates, we estimated three structural extensions incorporating clustering (*gwesp*) and degree distribution terms (*gwidegree*, *gdegree*) and compared coefficients across specifications (Additional file 2, Sect. 6.1-6.2). We also tested robustness across network subsets (cross-level ties only; excluding EU-level actors) and assessed multicollinearity between authority and influence using QAP correlations, Jaccard overlap, and coefficient stability diagnostics (Additional file 2, Sect. 6.5 and 6.7). The full R code, as well as the data files, is available in the Additional file 2 [44].

Results

The following results illustrate what researchers might expect to find when applying Net-Map methodology, rather than definitive conclusions about Romanian cancer prevention governance. The patterns described demonstrate the analytical capabilities of the combined

Table 1 ERGM parameter specifications for funding network analysis

Term	Label (parameter)	Interpretation
Baseline density	Edges (baseline)	This captures the overall tendency to form funding ties.
Same-governance level	Nodematch (level)	This tests whether actors at the same level (EU, national, local) are more or less likely to exchange funding. Given our focus on cross-level coordination, a negative coefficient indicates a preference for cross-level funding.
	Dyadic covariates (edgescov)	This incorporates other mapped relations as predictors of funding. These covariates test whether influence and authority co-occur with funding beyond baseline density and level structure.
Influence ties	edgescov (influence)	1 if <i>i</i> reports influencing <i>j</i> .
Authority ties	edgescov (authority)	1 if <i>i</i> has formal decision power over <i>j</i> .

Definitions and interpretations of exponential random graph model terms used to predict funding relationships in the Romanian cancer prevention governance network. The baseline density parameter captures overall tie formation tendency, while governance level homophily tests preferences for within-level versus cross-level funding coordination. Dyadic covariates examine whether existing authority and influence relationships predict funding ties beyond baseline network structure

Net-Map-ERGM approach. Table 2 reports the descriptive statistics of the networks generated by the panel of experts in the Net-Map exercise. Specifically, the Romanian cancer prevention governance network comprises 128 organizations distributed across three administrative levels: 63 national-level organizations (49.2%), 40 local-level organizations (31.2%), and 25 European-level organizations (19.5%).

The funding network exhibits low overall density (5.14%), with 836 observed funding relationships among

Table 2 Network structure and funding flow patterns in Romanian cancer prevention governance

Characteristic	Value	Characteristic	Value
Network Composition		Cross-Level Funding Patterns	
Total organizations	128	Within-level ties	239 (28.6%)
European level	25 (19.5%)	Cross-level ties	597 (71.4%)
National level	63 (49.2%)	Cross-level percentage	71.4%
Local level	40 (31.2%)		
Network Structure		Funding Flows by Direction	
		European → National	280 (17.8% density)
Total funding ties	836	European → Local	161 (16.1% density)
Possible dyads	16,256	National → Local	155 (6.2% density)
Network density	0.0514 (5.14%)	National → European	1 (0.1% density)
Reciprocity	0.01 (1.0%)	Local → National	0 (0.0% density)
		Local → European	0 (0.0% density)
Relationship Networks			
Authority ties	150	Relationship Overlap with Funding	
Authority density	0.0092 (0.92%)	Authority-funding overlap	43/150 (28.7%)
Influence ties	1,012	Influence-funding overlap	647/1,012 (63.9%)
Influence density	0.0623 (6.23%)		

Illustrative network structure and funding flow patterns in Romanian cancer prevention governance. These descriptive statistics demonstrate the type of insights that can be generated through Net-Map analysis. Here, we report descriptive statistics for the multi-level cancer prevention governance network (N=128 organizations across European, national, and local levels). Cross-level funding comprises 71.4% of all funding relationships, with European organizations showing the highest outward funding activity, connecting to 17.8% of national organizations and 16.1% of local organizations. Upward funding is virtually absent, confirming hierarchical resource distribution. Influence relationships show greater overlap with funding ties (63.9%) than authority relationships (28.7%), suggesting informal networks better predict resource flows than formal structures. Overall network connectivity=5.14%; reciprocity=1.0%

16,256 possible directed dyads. Reciprocal funding relationships are rare (1% reciprocity), indicating predominantly unidirectional resource flows. Two distinct relationship networks were mapped alongside the funding network. The authority network contains 150 formal hierarchical relationships (density=0.92%), while the influence network is substantially denser with 1,012 informal influence ties (density=6.23%). The influence network density exceeds the funding network density, suggesting that influence relationships extend beyond direct resource allocation patterns.

The funding network shows strong hierarchical coordination patterns, with 597 ties (71.4%) occurring across governance levels rather than within them. European-level organizations demonstrate the highest outward funding activity, directing resources to both national (280 ties from 1,575 possible connections, 17.8%) and local levels (161 ties from 1,000 possible connections, 16.1%). National-to-local funding is substantially lower (155 ties from 2,520 possible connections, 6.2%), while upward funding from local to national or European levels is virtually absent (1 tie total). This pattern claims a clear hierarchical resource distribution model where higher administrative levels fund lower ones.

The overlap between relationship types and funding patterns reveals important differences in how formal and informal mechanisms translate into resource allocation. Influence relationships show substantial overlap with funding ties (647/1,012, 63.9%), indicating that informal influence networks closely mirror actual resource flows. In contrast, authority relationships show limited overlap with funding (43/150, 28.7%), suggesting that formal hierarchical structures are less predictive of actual resource allocation than informal influence patterns.

These descriptive statistics illustrate that while formal authority structures exist, the governance network operates primarily through cross-level resource flows guided more by influence relationships than formal organizational hierarchies. Figure 2 visualizes these patterns across the three relationship types, and several features merit attention. First, the density contrast across panels is immediately apparent: Panel A (authority, 150 ties) is visibly sparse, Panel B (money, 836 ties) is intermediate, and Panel C (influence, 1,012 ties) is the densest (a visual gradient that previews the ERGM finding that influence has the strongest association with funding). Second, Panels B and C share similar spatial structure, reflecting the 63.9% tie overlap between influence and funding, whereas Panel A does not visually resemble Panel B, consistent with the lower authority-funding overlap (28.7%). Third, in Panel B, cross-level ties (solid arrows) dominate the visual field while within-level ties (dotted lines) are sparse, corresponding to the strong preference for cross-level funding (OR=0.35, $p<0.001$, for same-level in the

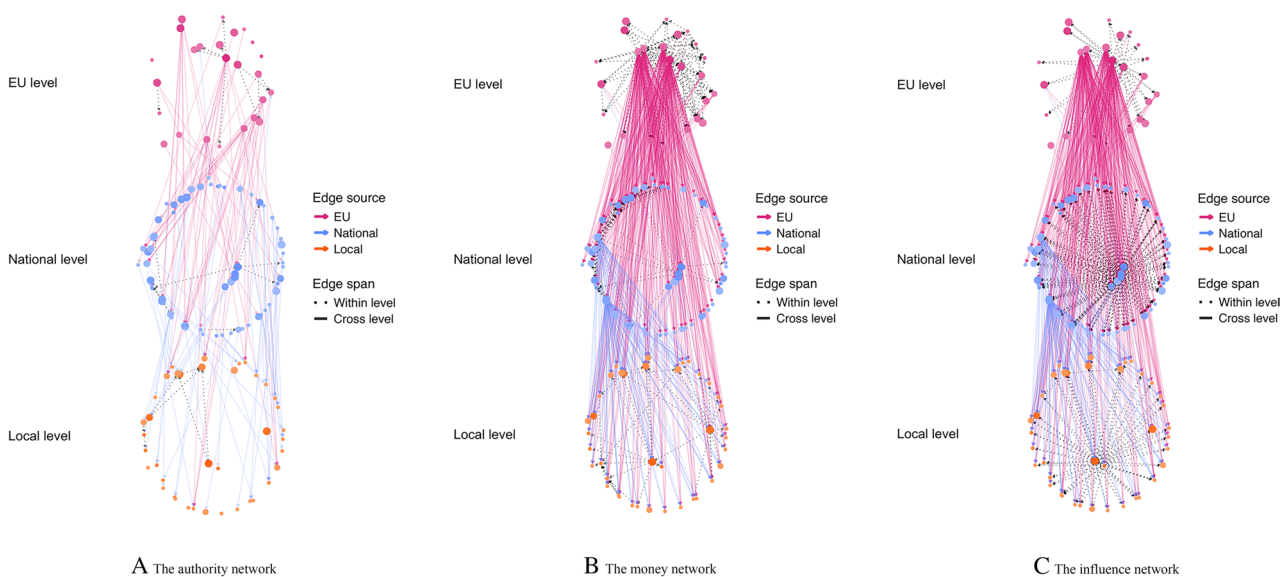


Fig. 2 Multi-level Stakeholder networks in primary prevention health policy: authority, financial, and influence relationships. Networks are organized by governance level (EU, National, Local), with nodes colored by level (EU = pink, National = blue, Local = orange). Solid arrows represent cross-level ties; dotted lines show within-level connections. **(A)** Authority network: 150 directed ties, sparse and concentrated among a few formal hierarchical relationships. **(B)** Funding network: 836 directed ties, dominated by cross-level flows from EU-level nodes (pink) toward national and local levels, with virtually no upward funding. **(C)** Influence network: 1,012 directed ties, the densest of the three panels, with spatial structure visually resembling the funding network; consistent with the 63.9% tie overlap between influence and funding. The density contrast across panels (**A** < **B** < **C**) and the structural resemblance between Panels **B** and **C** provide visual context for the ERGM results reported in Table 3

Table 3 Authority vs. Influence: Predictors of funding ties in health governance networks

Parameter	Model 1 Baseline	Model 2 Cross-level	Model 3 Authority	Model 4 Full Model
Edges (baseline)	-2.915*** (0.036)	-2.777*** (0.042)	-2.831*** (0.043)	-4.140*** (0.077)
Same governance level	—	-0.417*** (0.078)	-0.387*** (0.079)	-1.040*** (0.112)
[OR]	—	0.66	0.68	0.35
Authority relationship	—	—	1.989*** (0.185)	1.751*** (0.305)
[SE]	—	—	7.31	5.76
[OR]	—	—	—	5.127*** (0.106)
Influence relationship	—	—	—	168.54
[SE]	—	—	—	16.256
[OR]	—	—	—	16.256
Log-likelihood	-3295.0	-3280.1	-3238.2	-1615.6
AIC	6592.1	6564.3	6482.4	3239.3
BIC	6599.8	6579.7	6505.5	3270.1
Deviance	6590.1	6560.3	6476.4	3231.3
<i>n</i> (dyads)	16,256	16,256	16,256	16,256
<i>n</i> (edges)	836	836	836	836
<i>n</i> (nodes)	128	128	128	128

Exponential random graph models predicting funding relationships among 128 organizations in Romanian cancer prevention governance. Coefficients are shown with standard errors (in parentheses) and odds ratios [in brackets]. Influence relationships are the strongest predictor of funding ties (OR = 168.54; attenuated to 41.49 under structural controls; see Additional file 2, Sect. 6.2), while authority relationships show a stable, independent effect (OR = 5.76; range 5.76–6.46 across all specifications). Organizations prefer cross-level funding coordination (OR = 0.35). All models were estimated using MPLE. *N* = 16,256 dyads; 836 funding ties. ****p* < 0.001

ERGM). Fourth, Panel B reveals a concentration of outgoing ties from EU-level nodes, with dense downward arrows toward national and local levels and virtually no upward flow; a hub-spoke structure that the structural extensions (Additional file 2, Sect. 6.2) confirm through a significant out-degree heterogeneity term (gwodegree, OR = 0.01, *p* < 0.001), and which explains why the influence OR is attenuated from 168.54 to 41.49 when this degree concentration is statistically controlled.

To illustrate how exponential random graph models can be used to understand mechanisms driving funding relationships, we estimated a series of ERGM models (Table 3). We started with a baseline model (Model 1) containing only the network density parameter (edges), then sequentially added covariates in order of theoretical proximity to the dependent variable. Model 2 adds governance-level homophily, a structural feature of the multi-level architecture that may shape funding patterns regardless of specific inter-organizational relationships. Model 3 adds formal authority ties, the institutionally mandated governance channel through which funding might flow. Model 4 adds informal influence ties, the emergent relational dimension that theory suggests may operate alongside or beyond formal structures. This sequence allows each mechanism’s incremental contribution to be assessed while controlling for those already in the model.

The full model reveals several key patterns in network formation processes. Informal influence relationships

emerge as the dominant predictor of funding ties, with organizations connected by influence relationships being 168.54 times more likely to have funding connections ($p < 0.001$). Formal authority relationships also significantly predict funding, increasing the odds by 5.76 times ($p < 0.001$). The governance level parameter indicates a strong preference for cross-level coordination, with same-level funding relationships being significantly less likely ($OR = 0.35$, $p < 0.001$). Because the network is sparse (5.14% density) and degree distributions are heterogeneous, we assessed whether these estimates are robust to unmodeled structural dependencies. Supplementary structural extensions that control for transitivity and degree heterogeneity (Additional file 2, Sect. 6.2) attenuate the influence OR from 168.54 to 41.49 (Model 7, $\Delta AIC = -425.3$ vs. Model 4), while the authority OR remains stable across all specifications (range: 5.76–6.46). The same-level OR is also unchanged (range: 0.34–0.36). Thus, approximately three-quarters of the raw influence estimate reflects network structural features (hub-spoke patterns, clustering) rather than the influence covariate per se, but the effect remains large, highly significant, and the strongest predictor in every specification.

These findings suggest that influence and authority serve complementary roles in resource allocation: influence is the dominant predictor of funding ties, while authority provides a stable, independent contribution that is robust to model specification. The preference for cross-level funding coordination suggests that cancer prevention governance operates through vertical mechanisms rather than horizontal collaboration within administrative levels.

All ERGM models converged successfully using maximum pseudolikelihood estimation (MPLE). Parameter stability tests across different random seeds (12345, 54321, 99999) showed coefficient variation below 0.1 for all parameters, indicating highly stable estimates. Standard errors were successfully computed for all coefficients, enabling reliable statistical inference. Model comparison revealed substantial improvement from the baseline to full specification. The full model ($AIC = 3,239.3$) dramatically outperformed the baseline model ($AIC = 6,592.1$), representing an improvement of 3,352.8 AIC points. This consistent improvement indicates that relationship-based predictors capture fundamental network formation processes not explained by baseline density alone.

Specification sensitivity tests confirmed the necessity of both authority and influence predictors. Removing the influence network from the full model increased AIC by 3,243.2 points, indicating that this predictor is critical for model performance. Removing authority relationships increased AIC by 27.7 points, showing this predictor also

contributes meaningfully to model fit, though to a lesser degree than influence relationships.

To assess whether the dyadic-independence estimates are sensitive to unmodeled structural dependencies, we estimated three structural extensions (Additional file 2, Sect. 6.2). Model 5 adds transitivity (gwesp), which captures whether funding ties cluster into triads; in governance terms, whether organizations that share a common funding partner tend to also fund each other, reflecting coordinated funding circuits. Model 6 adds degree heterogeneity terms (gwidegree, gwodegree), which capture hub-spoke patterns in funding; specifically, whether a small number of actors (predominantly EU-level) send or receive disproportionately many ties. Model 7 combines all structural terms and provides the best fit ($\Delta AIC = -425.3$ vs. Model 4). The degree heterogeneity terms yield the largest improvement ($\Delta AIC = -392.3$ for Model 6), confirming that the out-degree distribution is far more concentrated than a dyadic model assumes ($gwodegree = -4.52$, $p < 0.001$). Substantively, this means the funding network is organized around a few dominant funders whose hub position inflates the raw influence estimate (a pattern visible in the concentration of outgoing ties from EU-level nodes in Fig. 2B). Once these structural features are controlled, the influence OR is attenuated from 168.54 to 41.49, while the authority OR remains stable across all specifications (range: 5.76–6.46) and the same-level OR is unchanged (range: 0.34–0.36). The influence effect thus remains the dominant predictor ($p < 0.001$ in all models), but approximately three-quarters of the raw estimate reflects network structure rather than the influence covariate per se. We retain the dyadic Models 1–4 as the primary specification because the nested progression illustrates the methodological workflow. However, the structural extensions confirm that all substantive effects are robust and identify degree heterogeneity as the main source of estimate inflation.

Goodness-of-fit testing using in-degree, out-degree, edgewise shared partner, and geodesic distance distributions (200 simulated networks) showed adequate fit, with 956 of 1,030 tests (92.8%) non-significant at the 0.05 level (Additional file 2, Sect. 6.1). The dyadic-independence specification does not incorporate higher-order structural dependencies (clustering, degree heterogeneity). Structural extensions adding these terms (Models 5–7; Additional file 2, Sect. 6.2) improve model fit substantially (best model $\Delta AIC = -425.3$) and confirm that all substantive coefficients remain significant, with the authority and same-level effects essentially unchanged. The influence OR is attenuated from 168.54 to 41.49 once degree heterogeneity and clustering are controlled, indicating that the raw estimate partly absorbs structural network features. Subset robustness tests (Additional file 2, Sect. 6.5) confirm that findings are not driven by

particular actor groups: authority independently predicts funding in the cross-level subset ($OR=6.72$, $p<0.001$), and results hold when EU-level actors are excluded. Multicollinearity diagnostics (Additional file 2, Sect. 6.7) show that authority and influence are empirically distinct (QAP $r=0.076$; Jaccard similarity = 0.034), ruling out mutual confounding.

All relationship parameters demonstrated high statistical significance ($p<0.001$) with adequate precision. The influence relationship parameter showed particularly high precision ($SE=0.106$), while the authority relationship parameter had moderate precision ($SE=0.305$). The cross-level preference parameter also showed high precision ($SE=0.112$), indicating reliable estimation of governance level effects.

The ERGM analysis reliably captures dyadic relationship patterns and their relative importance for funding tie formation. Goodness-of-fit is adequate for the modeled statistics, and the structural extensions confirm that the substantive conclusions (i.e., influence as the dominant predictor, authority as a stable independent complement, and a strong preference for cross-level coordination) are robust to alternative specifications and network subsets. The cross-sectional design limits causal inference about network formation processes. The models identify associations between relationship types and funding patterns but cannot determine whether influence relationships lead to funding or whether funding creates influence relationships.

Discussion

We demonstrate the methodological application of Net-Map to map governance of primary cancer prevention in Romania and illustrate how funding relationships can be modeled using ERGMs. This methodological demonstration reveals three types of patterns researchers might expect when applying this approach. First, funding may be predominantly cross-level: in this illustrative case, 71.4% of ties span EU, national, and local levels. Second, influence ties may emerge as the strongest correlate of funding. In this demonstration, the influence OR is 168.54 in the dyadic model, attenuated to 41.49 once network structural dependencies are controlled (Additional file 2, Sect. 6.2), but remains the dominant predictor across all specifications. Third, authority ties show a stable, independent contribution (OR range 5.76–6.46 across all models), and the two covariates are empirically distinct (QAP $r=0.076$; Jaccard overlap = 0.034). Same-level funding may be disfavored ($OR=0.35$, $p<0.001$) while the funding network remains sparse (density 5.14%). These illustrative findings suggest that resources flow downward and follow informal influence more than formal hierarchy. As an illustrative case, this analysis shows how influence appears to organize coordination

and access, acting as a practical mechanism for moving money across levels. The methodological demonstration indicates that authority and influence serve complementary functions: authority provides stable institutional scaffolding whose effect is robust across model specifications, while influence captures broader coordination patterns that are partly structural in nature. These patterns suggest that formal governance structures are not ineffective but serve a function distinct from informal influence. The two networks are nearly orthogonal (QAP $r=0.076$; Jaccard overlap = 0.034; Additional file 2, Sect. 6.7), meaning they capture largely independent dimensions of governance rather than competing explanations of the same phenomenon. This is consistent with research on health sector leadership showing that formal and informal dimensions of authority operate through distinct mechanisms [45]. Authority's coefficient is stable across specifications (OR range 5.76–6.46), whereas influence is dominant in magnitude but partly entangled with network structural features such as hub-spoke patterns and clustering. In the cross-level subset, authority independently predicts funding ($OR=6.72$, $p<0.001$; Additional file 2, Sect. 6.5). However, we note that the perfect correspondence between cross-level influence and cross-level funding ties (597/597) could partly reflect the expert panel's difficulty in distinguishing these constructs at the cross-level interface. Given the single-panel design, these patterns should be interpreted as suggestive of complementarity rather than as definitive evidence of how governance operates. The cross-level pattern indicates reliance on vertical linkages rather than horizontal collaboration within levels.

These patterns can be interpreted using multilevel governance and network governance theory, though the illustrative design limits such interpretation to hypothesis generation rather than theory testing. The dominance of cross-level funding (71.4%) and the near-absence of upward flows are consistent with the vertical coordination structures that MLG theory associates with Type II governance arrangements, where EU-level actors operate as funding hubs connecting to national and local implementers [22]. The near-orthogonality of authority and influence networks (QAP $r=0.076$) resonates with network governance arguments that formal and informal coordination represent distinct governance dimensions rather than points on a single hierarchy-to-network continuum [23]. The stability of authority's effect across model specifications, combined with the structural attenuation of influence, suggests that these mechanisms operate through different logics: authority provides consistent institutional scaffolding regardless of network structure, while influence is partly a reflection of actors' structural positions (degree, clustering). These observations are consistent with theoretical expectations, but

the single-panel, cross-sectional design means they cannot confirm or refute specific theoretical propositions. What the study does demonstrate is that the Net-Map-SNA workflow can generate the kind of structured, multiplex relational data that empirical tests of these theories would require. Future research with broader panels, multiple governance sites, and longitudinal designs could use this approach to test specific propositions. For example, whether Type II governance arrangements are associated with greater reliance on informal coordination, or whether the authority-influence balance varies systematically across health system types.

A further pattern exemplifies insights relevant for system design: EU-local flows (16.1% of possible dyads) are present but smaller than EU-national flows (17.8%). In this illustrative setting where influence strongly predicts funding, the relative paucity of direct EU-local ties and the lack of upward connections suggest weak feedback from implementers to EU programs. This example provides grounds to strengthen direct EU-local connectivity, not to bypass national roles, but to shorten paths, improve information flow, and align funding with delivery realities.

This illustrative analysis demonstrates three types of diagnostic insights that the Net-Map-ERGM approach can generate for decentralized health systems, i.e., patterns that warrant further investigation rather than immediate policy action. First, the methodology surfaces informal coordination channels that formal governance documentation may not capture. In this network, authority and influence are nearly orthogonal (QAP $r = 0.076$; Additional file 2, Sect. 6.7), suggesting they represent distinct governance dimensions. If confirmed with broader stakeholder panels and administrative records, this pattern would imply that relying solely on formal organizational charts misses how coordination actually operates. This is a finding that would justify incorporating participatory network mapping into program design to identify influential brokers whose role is institutionally invisible. Second, the approach reveals variation in governance coverage across levels. EU-national funding density (17.8%) exceeds EU-local density (16.1%), and national-local density is considerably lower (6.2%). Whether such gaps represent genuine vulnerabilities (where funding depends on informal channels that may be fragile if key actors change positions) is a question that requires validation with institutional data. Yet this is precisely the type of structural diagnosis the methodology is designed to produce. More broadly, health system reform research demonstrates that the relationship between governance mechanisms and system performance is not automatic; for instance, evidence from hospital-level analyses in Iran suggests that centrally initiated reform plans do not uniformly translate into improved local

performance, underscoring the importance of understanding how resources are actually allocated and coordinated at each governance level [46]. Third, the analysis identifies limited overlap between formal and informal governance channels. Only 38 of 1,124 combined governance ties involve both authority and influence (Jaccard = 0.034; Additional file 2, Sect. 6.7). This separation raises the question of whether cross-level funding has adequate accountability when governed by only one mechanism. Answering this question would require longitudinal data and multi-stakeholder validation, but the methodology flags it as a priority for system design.

These implications should be interpreted in light of the modeling constraints. The structural extensions (Additional file 2, Sect. 6.2) show that the influence-funding association, while consistently the strongest predictor, is attenuated by approximately 75% once degree heterogeneity and clustering are controlled. This means the raw Model 4 estimates overstate the magnitude (though not the direction or significance) of influence's role relative to authority. Under structural controls, the influence-to-authority ratio is approximately 6:1 rather than the 29:1 suggested by the dyadic model. This tempered estimate actually strengthens the policy relevance of authority: formal governance structures play a proportionally larger role than the raw estimates suggest, reinforcing the recommendation to align formal mandates with informal coordination patterns rather than treating authority as negligible. Similarly, the binary coding of ties means that the models cannot distinguish weak influence from strong influence; future implementations of the Net-Map approach that elicit ordinal tie strength would enable more precise estimates of how relationship intensity shapes resource allocation.

The primary contribution of this work is methodological. We demonstrate an end-to-end workflow linking participatory mapping to model-based inference. Net-Map generated a validated list of actors and ties. ERGMs then quantified which relations are associated with funding while accounting for interdependence. This illustration shows that the approach is transparent and reproducible and appears appropriate for decentralized systems where formal documents under-represent how decisions are made. Additionally, this methodological demonstration describes patterns of allocation rather than distributional fairness. We therefore refrain from equity claims. Future work should add explicit equity metrics (e.g., funding in-degree by level or sector; concentration indices) and relate them to prevention needs to test whether cross-level flows are also fair flows.

As an illustrative methodology demonstration, several important limitations must be emphasized. Most critically, the network reflects the perceptions of a single, highly embedded NGO panel. This methodological

choice prioritized demonstrating the complete research workflow over achieving representative findings. While this brings strong system knowledge for illustrative purposes, it creates significant risks of shared blind spots that limit generalizability. We mitigated this through scripted facilitation, consensus rules, triangulation with documents, and multi-session validation, yet residual bias is possible. The primary purpose of this analysis is to show how the methodology works rather than to provide definitive insights into Romanian health governance. The design is cross-sectional; therefore, causality cannot be inferred. Influence could enable funding, but funding could also create influence.

Additionally, all relationships are coded as binary (tie present/absent), which is inherent to the Net-Map consensus protocol. This coding treats weak and strong ties identically and may overestimate the apparent overlap between influence and funding networks if marginal influence ties that do not meaningfully shape funding decisions are given the same weight as strong ones. Valued network approaches using ordinal tie strength would provide more nuanced estimates.

ERGM goodness-of-fit is adequate for the modeled dyadic statistics (92.8% of tests are non-significant), though the dyadic-independence specification does not capture all higher-order structure. Structural extensions (Additional file 2, Sect. 6.2) improve fit and confirm coefficient robustness, but the influence OR is attenuated by approximately 75%. This indicates that the raw estimate partly reflects network structure rather than the influence covariate alone.

Several steps would extend this methodological approach. First, broaden participation to include government, clinical, and local implementers, followed by cross-panel comparison to achieve more representative findings. Second, link administrative data (budgets, grants, contracts) to the mapped ties to validate reported funding flows. Third, track change over time using repeated mapping or longitudinal models to examine how reforms, budgets, or EU initiatives alter governance patterns. Fourth, future modeling should address the structural and measurement limitations identified here: weighted or valued ERGMs using ordinal tie strength elicited during mapping would address the binary coding limitation; stochastic actor-oriented models (SAOMs) could model the co-evolution of funding, influence, and authority networks over time; and latent space or stochastic block models could capture hierarchical community structure that may not be fully represented by the three-level governance classification used here. Additionally, qualitative research on how informal leadership operates within health organizations [45] could complement network-based approaches by clarifying the mechanisms through which influence translates into

coordination and resource allocation decisions. These extensions would transform the illustrative demonstration into a comprehensive empirical analysis suitable for policy conclusions.

Conclusion

This methodological demonstration illustrates that primary cancer prevention governance can be analyzed through cross-level relationships in which informal influence aligns with funding flows but does not render formal authority irrelevant. The supplementary analyses suggest that authority and influence operate as complementary, largely independent mechanisms: authority provides stable institutional scaffolding, while influence captures broader but structurally attenuated coordination patterns. These patterns, if confirmed with broader stakeholder panels and administrative data, would carry implications for how decentralized health systems monitor governance: mapping informal networks alongside formal mandates, identifying gaps in formal governance coverage, and assessing whether influence and authority provide mutual oversight. This Net-Map-ERGM workflow demonstrates a diagnostic approach to surface these questions from participatory network data. Future applications with more representative samples and longitudinal designs would be needed to move from diagnostic insights to actionable policy recommendations.

Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CV	Coefficient of Variation
EC	European Commission
ECAC	European Code Against Cancer
EC	INOMED-Center for Innovation in Medicine (Ethics Committee)
ERGM / ERGMs	Exponential Random Graph Model(s)
EU	European Union
GDPR	General Data Protection Regulation
GOF	Goodness-Of-Fit
MCMC	Markov Chain Monte Carlo
MLG	Multilevel governance
MPLE	Maximum Pseudolikelihood Estimation
NGO	Non-Governmental Organization
OECD	Organization for Economic Co-operation and Development
OR	Odds Ratio
SE	Standard Error
SNA	Social Network Analysis
WHO	World Health Organization

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

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Authors' contributions

B.-E.M., M.-G.H., C.C., and M.G. contributed to the conceptualization of the study. Methodology was developed by M.-G.H., B.-E.M., J.L., and J.L.M. Data curation was carried out by C.C., J.L., J.L.M., and I.O., while data management was coordinated by M.-G.H., C.C., and M.G. Data collection was conducted by B.-E.M., M.-G.H., A.T.-L., I.O., and B.-A.V. Quantitative analysis was performed by M.-G.H., B.-E.M., J.L., A.T.-L., B.-A.V., and I.O., and qualitative analysis by J.L.M., M.G., C.C., A.T.-L., and B.-A.V. Visualizations were performed by B.-E.M., and A.T.-L. Writing - original draft preparation was made by all authors. Supervision was provided by B.-E.M. and M.-G.H., and project administration and correspondence were managed by B.-E.M., M.G., and C.C.

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Data availability

The dataset analyzed in the current study and the R code are made openly available, as an additional file, in the Zenodo data repository as Mihăilă, B.-E., et al. Replication data and code for stakeholder mapping and Net-Map health governance analysis. Zenodo <https://doi.org/10.5281/zenodo.17329450> (2026).

Declarations

Ethical approval and consent to participate

All research procedures complied with the Declaration of Helsinki and the European General Data Protection Regulation (GDPR). The study protocol was approved by the Ethics Committee of the Center for Innovation in Medicine (EC-INOMED Decision No. D001/09-06-2023 and No. D001/19-01-2024). Written informed consent was obtained from all participants. We anonymized personal identifying information after each interview and securely stored data on encrypted drives accessible only to authorized personnel.

Consent for publication

All authors have read and approved the final version of this manuscript and consent to its publication.

Competing interests

The authors declare no competing interests.

Author details

¹Department of Sociology, University of Bucharest, Panduri 90-92, Bucharest 050663, Romania

²Center for Innovation in Medicine, Theodor Pallady Blvd. 42J, Bucharest 032266, Romania

³Department of Computer and Information Science, University of Konstanz, Universitätsstraße 10, Konstanz 78464, Germany

⁴Department of Social and Cultural Anthropology, GRAFO, Universitat Autònoma de Barcelona, Bellaterra 08193, Spain

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