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ORIGINAL ARTICLE

Unpacking knowledge systems for collective action towards sustainability: a social network perspective

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Abstract

Achieving sustainability requires collective action by diverse stakeholders, facilitated by knowledge systems that integrate scientific, policy, and locally tested, place-based practical insights. As collective action and knowledge systems are usually analyzed separately, this paper explicitly examines this relationship, assessing the role of knowledge in shaping collective action within a network of 32 sustainability initiatives in Southern Transylvania, Romania. Using social network analysis (SNA), we explore the interplay between 12 types of knowledge- and action-related collaborative activities, while also drawing on complementary data on organizational knowledge and decision-making processes to contextualize our findings. Our results suggest that knowledge relationships serve as structural entry points for further types of collaboration, functioning as necessary relational preconditions, while strategic action for deeper societal change may depend on the development of informal relationships. We propose a working hypothesis on how network collaborations evolve from low to high-risk actions and from coordination to cooperation, as suggested by the hierarchical structure of collaborative engagement we observed.

Keywords Knowledge systems · Collective action · Social network analysis (SNA) · Knowledge-action network · Sustainability

Introduction

Scholars have long argued that steering social-ecological systems (SES) towards sustainability requires joint efforts by multiple stakeholders (Bodin 2017; Carr Kelman et al. 2023; Folke et al. 2005; Galaz et al. 2008; Holahan and Lubell 2022; Kofinas 2009; Lubell et al. 2010; Ostrom 2010). Such efforts, organized as collaborative environmental governance and collective action, are informed by knowledge that is constructed, interpreted and negotiated at the science-society interface (Jasanoff 2004; van Kerkhoff and Lebel 2006; Wiek et al. 2012). Consequently, knowledge systems are increasingly recognized as playing an important role in shaping sustainability outcomes, as arenas for knowledge exchange and co-production (Cash et al. 2003; Miller and Wyborn 2020).

We define a knowledge system as "a network of actors connected by social relationships, formal or informal, that dynamically combine[d] knowing, doing and learning to bring about specific actions for sustainable development" (van Kerkhoff and Lebel 2006, p. 630; van Kerkhoff and Szlezák 2016, p. 4604). This definition evolved from research related to agricultural knowledge and information systems (Röling and Engel 1991; Röling and Jiggins 1998), and highlights the roles of agents, practices, and institutions involved in knowledge processes, as well as their relationships (Cornell et al. 2013). The term *knowledge-action network* has also been used to describe multi-actor

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arrangements working towards sustainability, underscoring the dynamic interplay of knowledge, actions and outcomes (Barraclough et al. 2023; Muñoz-Erickson and Cutts 2016). In this study, we use "knowledge system" and "knowledge-action network" interchangeably, though the latter is the more specific term.

In sustainability science research, knowledge systems as networks have been discussed in multiple ways: some scholars have focused on the science-society interface, calling for stakeholder dialogue and greater community engagement in academic research (Cornell et al. 2013); others have elicited properties of knowledge systems that support the uptake of knowledge into policy processes (Cash et al. 2003; Sarkki et al. 2015) or enable sustainability transformations (Sokolova 2023); still, others in the collaborative governance literature have employed social network analysis to link structural properties of knowledge systems with observed outcomes (Bodin and Norberg 2005; Crona and Bodin 2006).

Despite growing interest in knowledge systems and multiple normative claims of their utility (Apetrei et al. 2021; Guido et al. 2022), empirical investigations of how such systems work and translate into collective action remain scarce. Prior studies tend to focus either on knowledge exchange or on generic collaboration (see Sect. "Knowledge systems as networks underpinning collective action"), rarely addressing the interlinkages between knowledge and action. This bears important analytical questions that go beyond implicit assumptions about the mechanisms through which knowledge and collective action relate to each other. Practically, it leaves governance actors without evidence-based guidance on which types of relationships to prioritize when strengthening knowledge systems for sustainability (Cornell et al. 2013). Further, there is a limited understanding of the processes that shape knowledge systems and their functioning (Fazey et al. 2013), primarily at the level of sustainability practitioners, i.e. *action*-oriented actors. Though knowledge and action are intertwined in practice, they need to be analytically distinguished if we are to examine how they co-occur and support one another within a functioning knowledge system.

To address these gaps, this study sets out to unpack the relational dynamics within knowledge systems spurring collective action, by providing new insights into the underlying processes and network structures. To do so, we mapped and analyzed the case of a knowledge system of a collaborative network of 32 sustainability initiatives and NGOs from Southern Transylvania, Romania. These actors have been working for many years on a regional scale to advance sustainability towards a shared co-created development vision (Fischer et al. 2019). As part of a long-term transdisciplinary engagement (Sect. "Transdisciplinary case study: sustainability initiatives in Southern Transylvania, Romania"), both the formation of stronger links between these actors, as well as their moderate success in revitalizing the area could be witnessed over time. Through this observed connection of knowledge systems and collective action, this is a suitable case for our purposes, i.e., tracing the relations between knowledge, collaboration and collective action dynamics.

This leads us to ask:

> *How are knowledge- and action-oriented relationships structured and interrelated within a collaborative sustainability network?*

Addressing this question moves the field beyond normative statements about the role of knowledge systems in transformations, instead contributing empirical evidence on which types of relationships underpin knowledge systems, how they are interrelated, and where governance actors might strategically invest to strengthen capacity for sustainability transformations.

Our research draws on previous related work (Lam et al. 2021) and employs a leverage points perspective (Abson et al. 2017; Meadows 1999, 2008). Leverage points refer to different levels at which interventions in a system can be made, ranging from material to ideational. Transferred to actor relations, the perspective can be used to categorize different types of ties according to the systemic "depth" of the collaboration. Lam et al. (2021) proposed twelve types of interactions, linking social-ecological system characteristics—such as parameters, feedbacks, design and intent (Abson et al. 2017)—to activities ranging from material-focused exchanges and information sharing, to joint policy action and deliberation on actors' or societal paradigms and values. Our study translates this to a knowledge system perspective. Specifically, we employ the same interaction types to examine how knowledge and information exchange relate to other forms of inter-organizational collaboration and ultimately collective action.

We begin by outlining key theoretical considerations. Then, we review insights from social network analysis relevant to understanding the formation and functioning of knowledge-action networks. Next, we provide details on our case study and methodology and we present our findings. Finally, we discuss our results within the broader frame of knowledge-action debates, emphasizing their societal relevance, as well as gaps to be addressed by future research.

Theoretical considerations

Towards defining knowledge

For our study, we conceive of knowledge as a resource pertaining to an external reality, which can be "held" by an actor, communicated to others (explicitly or tacitly), and enriched through interactions and as a result of new evidence. This definition adheres to an ontological realism perspective, but is also compatible with the co-production and sociology of knowledge literatures. We operationalize *knowledge* broadly, encompassing: (a) organized observations about the sustainability issues that actors are working on—we will refer to it as *information*; (b) information internalized by an actor as a result of network interactions and which leads to new understandings or insights, including about causal relations in the system of interest (Kakabadse et al. 2003; Rydin 2007)—this corresponds to *knowledge* in a narrow sense. We collected data on both *information* and *knowledge* because in a practitioners' network these concepts are difficult to disentangle (Tàbara and Chabay 2013; West et al. 2019). Further, we are not concerned with the origin or validity of the knowledge exchanged in the case study network, but take at face value the actors' interpretation of these concepts. This approach aligns with prior work that also employed an expanded notion of knowledge, which included basic information, deeper understanding, and the capacity to respond to and learn from observed dynamics (Enqvist et al. 2018).

Knowledge systems as networks underpinning collective action

Our study's aims are situated in the broader context of inquiries into how knowledge translates into action for sustainability. Scholarly debates range from broad critiques of science-society interactions (Cash et al. 2003; Clark et al. 2016; Kläy et al. 2015; van Kerkhoff and Lebel 2006; Zeigermann 2021) to practical applications on the role of knowledge in group collaboration and specific environmental management projects (Chapman and Schott 2020; Crona and Parker 2012b; Guido et al. 2022; Hegger and Dieperink 2014; Hommes et al. 2009). An understanding of knowledge systems as networks can bridge these two dimensions, with action-oriented organizations playing a crucial role in influencing the generation, access, sharing and use of knowledge across stakeholders (van Kerkhoff and Szlezák 2016). Informed by the social network analysis and collaborative governance literatures, our study thus brings quantitative tools and network concepts into an area of sustainability science where knowledge systems have rarely been operationalized or studied empirically.

As Wynne (1992) noted, public responses to scientific knowledge depend more on social relationships and networks than on trust in scientific institutions and credibility alone. Against this background, boundary and bridging organizations have been described as essential for brokering knowledge across groups (Crona and Parker 2012a; Offermans and Glasbergen 2015). Effective knowledge systems comprise many individual and organizational boundary spanners who facilitate information and knowledge exchange and mediate differences in values and perspectives (Cash et al. 2003). Such actors can be identified through analyses of their relationships using social network analysis.

Further, structural aspects of networks relate to both knowledge utilization and outcomes of collective action, insofar as they determine three main types of activities: (a) how information and resources are shared; (b) how social influence is exerted, possibly leading to value and behavioral changes, and (c) how coordination and cooperation are translated into concrete actions (Henry and Vollan 2014). For instance, in natural resource governance contexts, social interactions with researchers have been shown to influence policy makers' use of (scientific) knowledge in their natural resource governance work (Crona and Parker 2012a). Similarly, environmental management outcomes are strongly related to how knowledge is exchanged (Fazey et al. 2013). For example, in an agricultural context in Australia it was found that social network structures differed for incremental vs. transformational climate change adapting actors, with the latter having a much larger number of information network ties than the former (Dowd et al. 2014).

Lastly, knowledge transfer is not merely about factual information and data. It also involves the transmission of beliefs, practices and normative visions of what sustainability looks like and which actions should be prioritized (Muñoz-Erickson et al. 2010), often in ways that are interrelated. The transmission of such cultural and value-related traits can be facilitated by repeated interaction and long-term collaboration (Axelrod 1997). It is for this reason that we captured 12 different types of knowledge- and action-related relationships between the actors in our study network (see Sect. "Data collection"). The "knowledge-action network" terminology encapsulates precisely this complexity (Cash and Buizer 2005, Muñoz-Erickson and Cutts 2016; Muñoz-Erickson 2014), and we employ it to refer to the full set of mapped relationships (the multiplex network).

Relevant concepts and insights from social network analysis

Social network analysis (SNA) is a methodology for studying structural aspects of actor relationships (Robins 2015;

Wasserman and Faust 1994) and has recently seen increasing application in policy and governance studies (Barnes and Bodin 2025; Berardo and Lubell 2019; Berardo et al. 2020; Bodin 2017; Bodin and Prell 2012; Fischer and Ingold 2020). In the sustainability literature, SNA has been used, among others, to explore power dynamics and social influence (Adams et al. 2018), to identify key actors who connect various sub-groups (Vance-Borland and Holley 2011), to analyze processes of collective learning (Newig et al. 2010), and to evaluate governance performance (Yi 2018). Applied to knowledge systems, SNA can elicit which actors are regarded as most knowledgeable, how knowledge is distributed, and how connectivity patterns influence knowledge sharing (Muñoz-Erickson and Cutts 2016).

Within sustainability research, few studies have explicitly looked at the role of knowledge in networks of collective action. Previous research suggested that fragmented information and knowledge exchange is associated with uncollaborative outcomes or ineffective resource management (Bodin and Crona 2008). Further, although multiplex relations are often investigated in governance research (Berardo et al. 2020), to our best knowledge, no study has taken a knowledge systems perspective, where *knowledge*- and *action*-specific ties are operationalized separately and their interplay analyzed. The novelty of our approach is that we differentiate between these ties and examine the network structures comparatively.

Following Borgatti and Foster (2003), two complementary and well-established perspectives from the SNA literature help conceptualize how knowledge-action networks operate, distinguished by the direction of causality. The first, which asserts that structure determines outcomes and examines the consequences of network structures, is our primary analysis lens. The second concerns the causes of network structures, looking at how networks are formed as a function of actor attributes; we draw on this more selectively, merely to help interpret observed patterns.

The structuralist paradigm emphasizes that human behavior is shaped by the social structures from which it emerges. According to this view, an actor's position in the network can either constrain or enhance their opportunities for action (Borgatti and Foster 2003), by affecting their access to resources, influence, and the ability to foster collaboration. Against this background, a critical question for social-ecological systems has been whether an ideal network structure for fostering collective action for sustainability exists. Although different networks have occasionally produced similar outcomes (Bodin et al. 2017), there is emerging evidence that successful networks balance exploitation and exploration configurations, i.e. connections within subgroups (*bonding ties*) and across different groups (*bridging ties*), respectively (Newman and Dale 2005; Yi 2018), with moderately connected networks performing best at identifying problem solutions (Lazer and Friedman 2007). Classic theories, such as the "strength of weak ties" (Granovetter 1973) and "structural holes theory" (Burt 1992), emphasize the advantages of weak ties for accessing diverse, nonredundant, and codifiable information across different parts of the network (Adler and Kwon 2002; Borgatti and Halgin 2011). Conversely, strong ties (close, frequent interactions) enhance trust within subgroups and facilitate the transfer of complex and tacit knowledge (Hansen 1999).

From this perspective, distinguishing between different knowledge- and action-oriented types of ties allows us to examine whether these forms of collaboration are associated with different structural configurations and how these might be interrelated within the same network.

Studies on bonding and bridging ties have also been framed in terms of a coordination vs. cooperation game. In coordination, where actors' values and interests are aligned, centralized but sparse networks appear sufficient for fostering joint action. In cooperation, where negotiation and opinion sharing are required, dense networks with triadic closure (where a friend of a friend is also a friend) are better suited, as they help develop mutual trust (Bodin 2017; Yi 2018). These structural configurations have often been interpreted through the risk hypothesis (Berardo and Scholz 2010), which posits that low-risk coordination problems are best managed through sparse, bridging-dominated networks, whereas high-risk cooperation problems benefit from denser, bonding-based configurations that provide assurance against defection. However, more recent work challenges this strict dichotomy, suggesting that both tie types are essential and often co-evolve as part of dynamic trust-building processes (Bodin 2017; Bodin et al. 2020).

From a knowledge-action network perspective, this evolving view is relevant insofar as knowledge and action-related collaborations may each involve different levels of coordination, negotiation and relational risk and commitment. Inspired by this literature, we suggest that examining the embeddedness of different knowledge- and action-oriented ties allows us to move beyond describing individual network structures towards understanding how different forms of collaboration co-occur and potentially support one another.

The second strand of the SNA literature focuses on how networks are formed as a function of actors' attributes and characteristics (Borgatti and Foster 2003; Borgatti and Halgin 2011). Processes such as reciprocity, proximity and homophily are used to explain how and why actors form ties (McPherson et al. 2001). Beyond these, centrality can also reflect resource asymmetries among actors (Burt 1992) or preferential attachment (Barabási and Albert 1999). In the context of knowledge exchanges, theories of identity and transfer highlight how social homogeneity can enhance communication and sharing (Cross et al. 2001; Reagans and McEvily 2003). In our study, these perspectives inform our discussion of the observed correlations between the different types of interactions (Sect. "Actor profiles and knowledge practices"), and help us interpret the qualitative data collected on organizational knowledge and action practices (ESM S9).

Geographic proximity has been shown to facilitate repeated (face-to-face) interactions and trust building for coordination purposes (Gerber et al. 2013; Mewhirter and Berardo 2019). For instance, Hileman and Lubell (2018) found that actors located in the same country or operating at the same geographic level exhibited a high propensity for network closure, i.e. were rather densely interconnected, with a higher than average local clustering coefficient. Also, while local actors were forming tight clusters, regional ones were helping bridge local groups, by enhancing resource sharing and cross-scale cooperation. The spatial dimension is particularly important in environmental governance, where shared geographic spaces tend to reflect biophysical interdependencies (Mewhirter and Berardo 2019), while local ecological knowledge and place-based issues need to be linked to national and international processes (Cash et al. 2003).

Similarly, *homophily*, or homogeneity among actors, has been shown to promote shared ideals and support coordination, while heterogeneity fostered innovation and the diffusion of new practices (Bodin et al. 2017). Homophily can reduce conflict and provide the basis for transferring complex and tacit knowledge, but it can also lead to redundancy, limiting the diversity of information (Prell et al. 2009). For example, in fishery systems, users predominantly shared information about the state of the resource within their occupational subgroups, leading to segmented knowledge flows (Crona and Bodin 2006, 2011).

Overall, the concepts reviewed above provide the analytical toolkit we draw on to examine how knowledge- and action-oriented relationships are structured and interrelated in our case study network. Rather than advancing new network theory or testing mechanisms of network formation, our approach applies insights from the SNA literature to operationalize knowledge systems and investigate empirically how they function in practice.

A leverage points perspective on actor relationships

The preceding sections establish that collaborative relationships in knowledge-action networks span from material resource exchanges to the transmission of beliefs and normative visions of sustainability (Sect. "Knowledge systems as networks underpinning collective action"), and that different types of ties between actors involve qualitatively different levels of coordination, trust, and relational risk (Sect. "Relevant concepts and insights from social network analysis"). To structure this spectrum for empirical application, we draw on Meadows' (1999, 2008) leverage points framework, as aggregated by Abson et al. (2017) into four system characteristics: parameters, feedbacks, design, and intent. Originally developed to identify where interventions in complex systems produce the greatest change, the framework has been recently employed as a heuristic in an increasing number of settings, from governance and institutional change (Chan et al. 2020; Davelaar 2021; Nerland et al. 2025; Rosengren et al. 2023), to entrepreneurship and business innovation (Caravelli-Svärd 2025; Luederitz et al. 2023), food system transformation (Scheuermann et al. 2024) and transdisciplinary research (Schäpke et al. 2024).

The leverage points framework, as applied here, serves to formulate different types of collaborative activities, ranging from simpler material exchanges to more complex political and value-based joint initiatives, all of which are required for systems transformation. In adapting this heuristic, the four Abson et al. (2017) categories were interpreted as corresponding to qualitatively different actor relationship types, each implying different types of relational commitments (Table 1) with direct relevance for the study of knowledge systems and collective action. The last column of Table 1 directly matches the twelve types of ties investigated in this study. The system of reference, in this case, is the broader social-ecological system within which the collaborative knowledge-action network is trying to intervene towards a sustainability transformation (see Sect. "Transdisciplinary case study: sustainability initiatives in Southern Transylvania, Romania"). Our operationalization was informed by our extensive engagement with the initiatives, prior field experience, and orientation interviews, ensuring that each leverage point reflected meaningful distinctions in practice. Lam et al. (2021) validated the use of our data collection instrument for this particular network, and the described approach allows us to map the multiplex network underlying a knowledge system. Our mapping to Meadows' framework should be understood as mutable and providing conceptual scaffolding rather than a deterministic and final classification.

Methods

Transdisciplinary case study: sustainability initiatives in Southern Transylvania, Romania

The case reported here was part of a transdisciplinary (TD) research process in Romania, which took place over several

Table 1 Twelve types of actor relationships mapped on the Leverage Points framework of Donella Meadows (2008) and Abson et al. (2017) levels of system interventions

Abson et al. (2017) System Intervention Category	Actor Relationship Type: Underlying assumptions in applying the heuristic	Leverage point	Short tie name	Details of relationship type (survey wording)
Parameters: interventions at this level target *quantifiable system properties* such as adjusting values of material stocks, rates of material flows, capacities to absorb shocks and physical structures	**Transactional relationships**: Systems interventions at the parameter level are considered to require actor relationships focused on the joint mobilization of tangible resources, through resource sharing and applied projects.	**LP1**	**Sharing material resources and tools**	Sharing material resources and tools with other organizations (e.g., office space and equipment, cars, event spaces and venues, facilitation materials)
		LP2	**Developing project applications**	Developing project applications and applying for funding or sponsorships together
		LP3	**Implementing projects together**	Implementing projects together (e.g., organizing workshops, creating development strategies or plans)
Feedbacks: interventions at this level target *the interactions* between stocks and flows that drive system dynamics, including learning and adaptive responses (via information feedbacks)	**Communicative and epistemic relationships**: For collective action to be able to target adaptive responses to system feedbacks (by enhancing balancing loops, altering self-reinforcing feedbacks, or dealing with delays), actor relationships around epistemic and sense-making dimensions are assumed as prerequisites.	**LP4**	**Exchanging information**	Exchanging information (e.g., by email, phone, or in person)
		LP5	**Acquiring new knowledge**	Acquiring new knowledge (i.e., learned useful things) from interactions and information exchanges with the other organizations
		LP6	**Exchanging informal advice**	Exchanging informal advice (i.e., asked for opinion) to make decisions
Design: interventions at this level target the *governance* of information flows, rules, and self-organization; they concern who controls system structure and decision-making	**Institutional and political relationships**: Action to redesign the system in which the collaborative network is embedded is considered to require actor relationships related to participation in governance arenas and joint rule-changing, including attempts to reorganize power structures (e.g. by changing exogenous network structures, including the governance of broader information flows).	**LP7**	**Meeting in policy processes / groups**	Meeting each other as participants in the same policy processes (e.g., public consultations) or institutional groups (e.g., industry boards, steering committees, associations)
		LP8	**Working to change policies**	Working together to change policies (e.g., through collaborative lobbying, coalitions, or joint petitions, and legislative proposals)
		LP9	**Setting up new collaborations**	Engaging together in setting up new collaborations with other organizations or actors (e.g., state actors, businesses, research institutions, communities, and associations)
Intent: interventions at this level target the *goals, paradigms, and values* that organize the system and inform what actions are pursued	**Deliberative and transformative relationships**: Action to redefine system goals and paradigms is understood here to require relationships that involve alignment on end-goals and missions, strategies, and the underlying values and worldviews that define the organizations in the collaborative network. Relationships that contribute to the joint surfacing of organizational values (Horcea-Milcu et al. 2019) are seen as a stepping stone towards system interventions at the intent level.	**LP10**	**Pursuing similar strategies**	Pursuing similar strategies in work
		LP11	**Reflecting jointly on mission and goals**	Reflecting jointly on mission and goals
		LP12	**Jointly reconciling values and worldviews**	Engaging jointly in activities that help reconcile differences in values and worldviews

Highlighted columns are directly reflecting the data collection instruments (see also Lam et al. 2021) and inform the analyses below. The leverage points sequence is reversed compared to the original numbering by Meadows (2008). This is because it reflects the question order in the surveys administered for data collection

years (2012–2019) and entailed regular face-to-face interactions between researchers and local practitioners to co-create solution options to foster the sustainability transformation of the region (Abson et al. 2017; Lang et al. 2012). We note that the authors have been closely involved in the transdisciplinary engagement with these actors over several years, which informed both the study design and the interpretation of results. The study area borders the Northern side of the

Central Carpathians, and is roughly demarcated by the cities of Brașov, Făgăraș, Sibiu, Târgu Mureș and Miercurea-Ciuc (Fig. 1). This is a predominantly rural and hilly region, with a heritage of rich cultural diversity, and where nature and human activities have co-evolved over centuries to shape the landscape into a mosaic of villages and highly biodiverse, low-intensity agricultural areas (Horcea-Milcu et al. 2018; Loos et al. 2016).

Recently, rural outmigration, agricultural intensification and lifestyle changes have been threatening both local ecosystem biodiversity and rural livelihoods (Loos et al. 2016). In response, numerous civil society initiatives, many constituted as non-governmental organizations (NGOs), have emerged, aiming to promote sustainable development through activities related to: nature and heritage conservation, support for small-scale farming, promotion of agro- and eco-tourism and rural community development. These initiatives pursue a common vision of balanced social and economic progress, which does not compromise on ecological integrity. In a previous project, a scenario planning exercise explored four potential futures for the region (Fischer et al. 2015, Fischer et al. 2019) and local actors selected the "Balance Brings Beauty" scenario as a guiding vision. Many of the initiatives also collaborate within an eco-destination region, coordinating activities across thematic and geographic boundaries to advance the transformation toward this balanced future. Pursuing this goal and vision requires not only collective action, but also knowledge about the necessary interventions, coordination among players, and the broad support of a wide range of stakeholders.

To understand how these efforts are supported by knowledge, we analyzed the network of 32 core sustainability initiatives (Fig. 1). NGOs play an important role as organizers of links between resource users and policy processes, facilitating ecosystem co-management across geographical and governance scales (Halls et al. 2005). Further, this case is suitable to our analysis, as previous research has already shown the relevance of the relationships in this particular network for fostering the sustainability transformation of the region (Lam et al. 2021).

Data collection

We employed a mixed methods approach, aligning with calls for integrating diverse methodologies when studying knowledge transfer and use (Crona and Parker 2012a). Data were collected through two surveys: one eliciting different types of network ties, and a second complementary survey, collecting details about knowledge-action processes at the level of each organization. To avoid stakeholder fatigue, the surveys were designed for multiple research purposes within the broader departmental project, and we only describe here relevant items for this study (see "Electronic Supplementary Material"—ESM S1). In addition, our interpretation draws on comprehensive data collected throughout our long-term transdisciplinary engagement in the case region (Fischer et al. 2019).

The **main survey**, focusing on social network data, was sent to 32 sustainability initiatives, out of which 30 responded. The actor list was initially produced during TD case scoping and subsequently validated with the stakeholders. The survey was administered online between December 2017 and February 2018. Non-responding organizations were later visited and assisted for online completion. For four organizations with multiple responses, data were aggregated by selecting the highest value reported for each variable. Lower values were assumed to reflect limited knowledge about collaborations from the respondents'

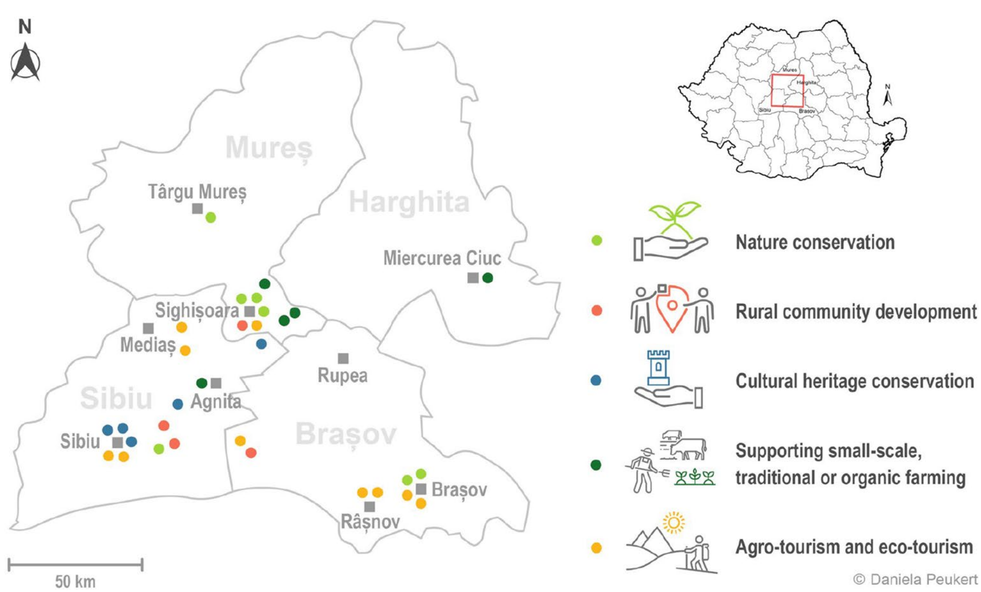

Fig. 1 Map of 32 action-oriented sustainability initiatives and their thematic areas of focus [map by Daniela Peukert, reprinted here from Lam et al. (2021), CC-BY 4.0, https://creativecommons.org/licenses/by/4.0/.]

respective roles. Variations in responses typically indicate that some respondents are better positioned than others to provide accurate information. In cases where a single response was obtained, this came from key figures like the director or founder, for whom high accuracy could be reasonably assumed. Weighted, directed data were collected for 12 types of relationships (Table 1). Additional attributes, such as size of organization, regional and topic focus were also collected to characterize the actors (Sect. "Actor profiles and knowledge practices").

After filling in the main survey, respondents could opt into the **second survey** to provide more details about their organizations' practices. Relevant items to this study comprise open and closed questions about knowledge processes (external and internal knowledge production and dissemination) and decision-making (stakeholder consultation, impact analysis, identification of alternative solutions, prioritization of actions, decision-makers), as detailed in ESM S1. This data serves to contextualize and help interpret the structural patterns observed in the network analysis, rather than constituting a separate line of investigation. There were 17 responses recorded, out of which 15 corresponded to 11 organizations from the core network of 32 (34%) and two from other organizations that found out about the survey via indirect channels and also responded to it. To provide qualitative context to the social network data, we also report on non-core actors' data.

Data analysis

Missing data

We employed R version 4.4.0 for all data analyses (R Core Team 2024). For network data, non-responses (including "I don't know" answers) were treated as absent ties (value = 0). Smaller networks, like in this study, have been shown to be relatively robust to moderate levels of missing data (up to 40%), as limited network size often leads to uneven tie distributions and, on average, higher centralization, which can stabilize several network-level measures (Huang et al. 2018; Huisman 2009). In our case, missing data levels were below 15%, with the exception of LP10 (30%) and LP11 (23%) due to high levels of "I don't know". However, when recalculating missingness for the responding subnetwork only (i.e. excluding ties of 2 out of 32 non-responding organizations), missing data dropped below 3% and for seven networks even below 1% of the total links. This information is reported to indicate that responses among participating organizations were highly complete. To check for robustness, the no imputation model was compared to an imputation model via the reconstruction method, and the results were fairly stable, as expected (ESM S2).

Preliminary analyses

Further, tie responses were dichotomized (i.e., treated as present or absent) to simplify analysis and improve comparability across networks. Because most organizations were represented by a single respondent, weighted tie values were difficult to compare meaningfully across actors and interaction types. Dichotomization thus provides a more robust approach for examining structural patterns across the twelve networks.

We treated each of the 12 types of relationships as a distinct network and standard metrics were computed (Table 2) using the *igraph* (Csárdi and Nepusz 2006; Csárdi et al. 2024), and *sna* packages (Butts 2023).The goal was to characterize and compare interaction patterns rather than infer causal effects. Betweenness centrality was calculated primarily to visualize structural differences across the networks (Fig. 2). This metric quantifies the extent to which an actor is on the shortest pathway between all other pairs of actors (Freeman 1978; Wasserman and Faust 1994), and it has been used as an indicator of information brokerage and control. Actors with high betweenness possess critical ties and can transmit knowledge efficiently, which positions them as potential brokers in the network, but they also have the power to modify and distort flows, influencing others (Brass and Burkhardt 1993).

Finally, to evaluate whether the observed structural properties of the empirical networks were driven by chance or reflected meaningful underlying processes, we followed Levy and Lubell (2018) and compared our case data with random graph models (Sect. "Patterns of knowledge-action collaboration"). While conditional dependencies are not modelled, random graph comparisons offer a useful baseline for interpreting descriptive metrics and for making cross-network comparisons in a multiplex setting. For each type of network (LP1-LP12), we generated 1000 Erdős-Rényi random graphs with sizes and edge densities matching those of the empirical networks (also discussed in Lusher et al. 2013). We then computed the same metrics and used the obtained value distributions as a baseline for comparison (Fig. 3). To assess the significance of deviations of our empirical data we employed a percentile-based approach (i.e., at 0.05% significance level, we calculated the 2.5th and 97.5th percentiles). This methodology is robust to non-normal distributions and extreme values. Outlier values in the empirical data indicate that the observed network structure is unlikely to have emerged by random processes alone, but is explained by underlying social dynamics.

These preparatory analyses ensure that subsequent examinations of cross-network correlations and hierarchical structures reflect meaningful patterns rather than artifacts of

Table 2 Descriptive measures for 12 LP networks

Network	Number of ties	Density	Connectedness	Centralization [in-degree]	Centralization [out-degree]	Average path length	Global clustering coefficient
LP1 Sharing material resources and tools	399	0.402	1	*0.217*	0.617	1.651	0.692
LP2 Developing project applications	*211*	*0.213*	1	0.247	**0.779**	**2.097**	0.501
LP3 Implementing projects together	244	0.246	1	0.246	0.745	**2.029**	0.552
LP4 Exchanging information	**453**	**0.457**	1	**0.394**	*0.528*	*1.545*	**0.728**
LP5 Acquiring new knowledge	**445**	**0.449**	1	**0.369**	*0.569*	*1.522*	**0.722**
LP6 Exchanging informal advice	338	0.341	1	0.348	0.647	1.713	0.620
LP7 Meeting in policy processes / groups	398	0.401	1	0.352	0.618	1.641	0.715
LP8 Working to change policies	255	0.257	1	0.234	0.767	1.888	0.586
LP9 Setting up new collaborations	258	0.260	1	*0.231*	0.764	1.876	0.595
LP10 Pursuing similar strategies	331	0.334	1	0.288	0.655	1.692	0.643
LP11 Reflecting jointly on mission and goals	259	0.261	1	0.263	0.763	1.884	0.584
LP12 Jointly reconciling values and worldviews	*239*	*0.241*	1	0.251	**0.784**	1.827	0.572

For each type of network, the top two highest values are shown in bold; lowest two values are shown in italics. Metrics are shown for unweighted directed ties

missing data, structural variable non-independence or measurement variability.

Main approaches

To examine the interplay between different types of interactions, Pearson's product-moment correlations between the networks were computed and assessed using the Quadratic Assignment Procedure (QAP). By utilizing permutation tests to rearrange matrix data, QAP determines the significance of observed correlations. Because it does not require variables to be independent, QAP is particularly suited for statistically analyzing complex relational data (Baker and Hubert 1981; Krackhardt 1987). To synthesize structural relationships among the multiple networks, we complemented the QAP correlation analysis with metric Multidimensional Scaling (MDS) and Guttman scaling (*stats* and *guttman* packages, respectively; see Libura 2024; Mardia 1978). QAP correlations quantify the extent to which tie patterns overlap across the same set of actors, while MDS offered a distance-based representation of the dissimilarities between networks, as captured in a two-dimensional space, allowing us to identify clusters or gradients among interaction types. Lastly, we ran a Guttman scaling procedure on the dichotomized matrix of 12 types of ties (31*32 rows x 12 columns), which revealed hierarchical structures among the different relationships. Guttman scaling is based on cumulative scaling logic, assessing whether interaction types can be arranged along a single hierarchical dimension in which ties higher on the scale imply the presence of ties lower on the scale, thereby revealing whether collaboration domains form a systematic progression within the knowledge-action network. All these analyses are descriptive insofar as they summarize patterns of structural similarity, rather than identify causal mechanisms of tie formation or actor motivations.

Additionally, we summarized and interpreted the data on knowledge processes and decision-making from the additional survey, in order to contextualize the observed network structures. Data on actor profiles were used to qualitatively enrich our discussion ("Discussion"). While ERGMs or other inferential models could explicitly test formation processes, the small network size and focus on multiplex relationships made descriptive comparisons, correlation analyses, and hierarchical scaling the most suitable approach for this study.

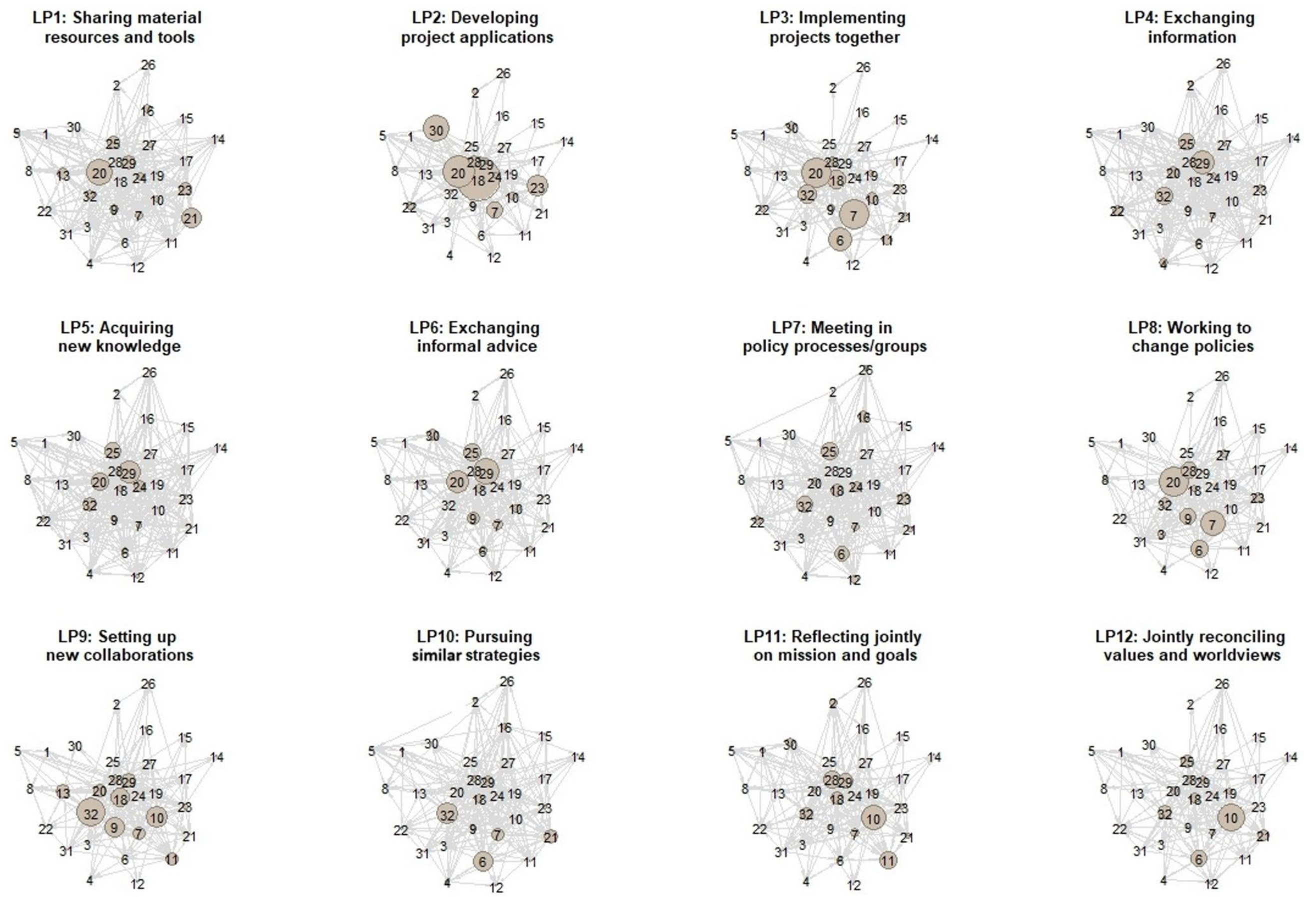

Fig. 2 Structure of 12 LP networks. Size of nodes is proportional to betweenness centrality values. Shown here are unweighted directed ties. For further differentiation of the 12 networks, please refer to ESM S6

Results

Actor profiles and knowledge practices

Details of network actor profiles and their self-reported organizational characteristics are included in ESM S3 and S4. More than half of the organizations are very small, with up to five employees (18 organizations, 56.25%), followed by medium-sized ones with between 6 and 10 employees (10 organizations, 31.25%), and then larger ones, with more than 10 employees (4 organizations, 12.5%).

Geographically, within the five counties delimiting the case study region, most organizations reported activities in: Sibiu county (with 84.4% of the organizations), followed by Brașov (65.6%), Mureș (59.4%), Harghita (31.5%) and Covasna (28.2%). About half of the organizations have a rather local focus (one or two counties), while the other half operate regionally, spanning three or more counties.

The self-reported thematic priorities reflect a general focus on rural community development (56.3%) and agro- and ecotourism (50%), followed by nature conservation (46.9%), supporting small-scale farming (43.8%) and cultural heritage conservation (37.5%).

Additional insights from the complementary survey on knowledge processes and decision-making provide context for the network patterns discussed below (Sect. "Patterns of knowledge-action collaboration"). Organizations vary in their approaches to internal and external knowledge acquisition, stakeholder consultation, and impact reflection, highlighting a heterogeneous landscape of strategies and capacities. Some actors actively produce and disseminate knowledge, while others rely more on trust-based relationships and prior collaborations to collect the information required for their decisions. Given the low response rate of the complementary survey (11 out of 32 core organizations) and the exploratory nature of this study, a quantitative linking of actor attributes to network position was not feasible. Instead, these insights are used qualitatively to help interpret correlational analyses, as well as the role of proximity and homophily in shaping interactions (see details in ESM S9).

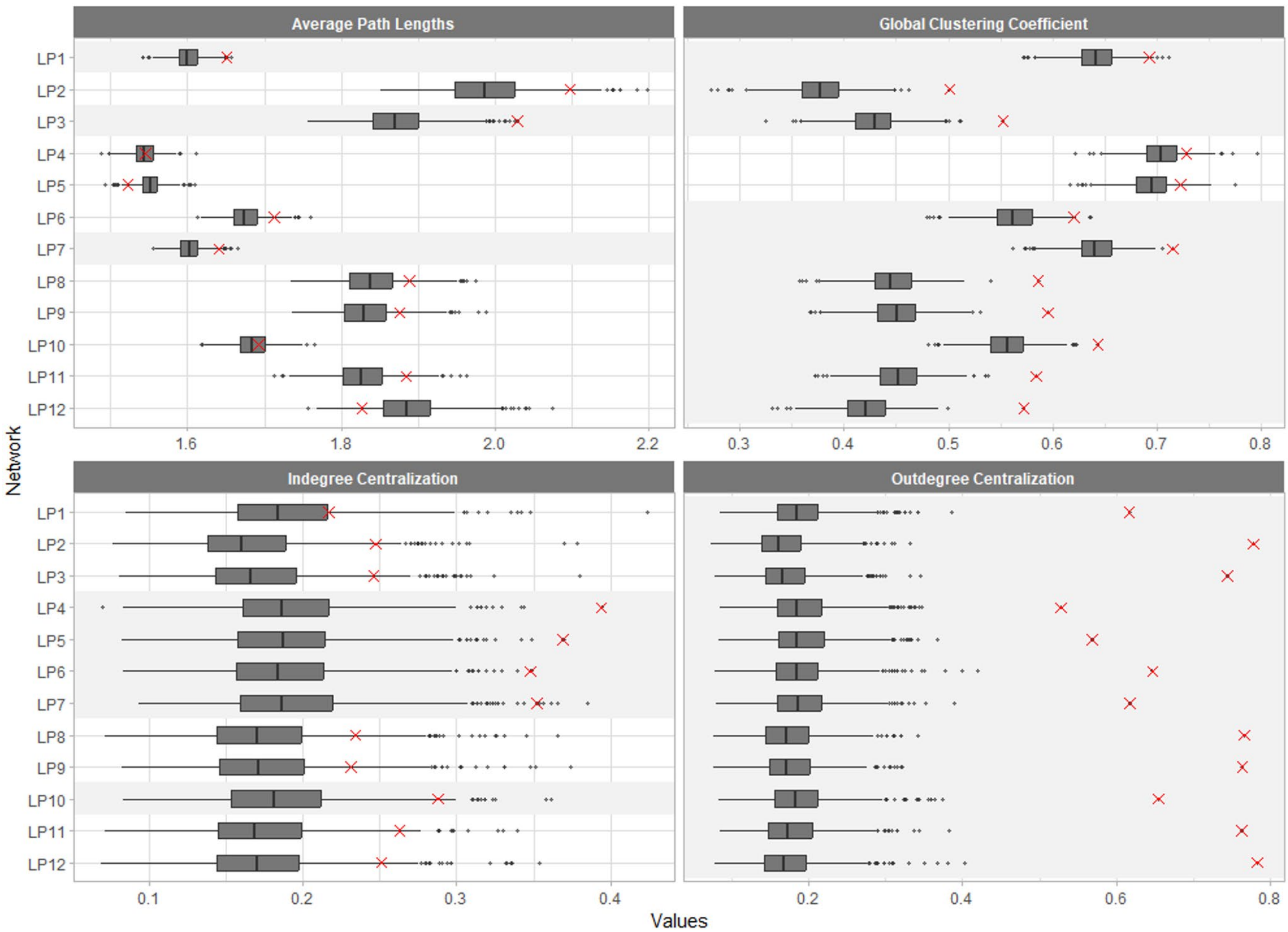

Fig. 3 Metrics of Random Graphs vs. Empirical Networks. The "X" symbol marks the corresponding value of the respective empirical network for the shown metric. Cases where the empirical value deviates significantly from the distribution of values in the random graphs are highlighted in grey ($p<0.05$). See also ESM S7

Patterns of knowledge-action collaboration

General metrics and comparisons with random graphs

The 12 graph structures (Fig. 2) and the general network metrics (Table 2) reflect a well-connected knowledge-action network. For all types of relationships, graph connectedness is 1, meaning that no organization is isolated (all can be reached from every other node). The number of ties and densities of the directed networks indicate that, while many connections exist, there is potential for more collaboration. Densities for the undirected networks were somewhat higher, with values between 0.331 (LP2) to 0.599 (LP5) (ESM S5). We triangulated our findings by conducting additional analyses on the networks with mutual ties only, including computing correlations, and overall found similar results (ESM S5-S7).

The significance and implications of the other metrics in Table 2 are evaluated via comparisons with the simulated Erdős–Rényi random graphs (Fig. 3). Values falling outside the 95% confidence range (highlighted in grey) signal that the observed network structures are unlikely to have emerged by chance alone, but instead reflect underlying social processes.

Overall collaborative landscape At first glance, the relatively low in-degree centralization values in Table 2 suggest that no actors are extremely prominent, and most are perceived as relatively equal in terms of how others rely on them. However, networks related to information and knowledge exchange (LP4 and LP5), advice exchange (LP6), policy participation (LP7) and joint strategizing (LP10) show values outside the confidence intervals of the random graphs. This indicates that some organizations are disproportionately sought out in these domains, which points to potentially specialized roles in the network in facilitating these types of interactions.

In contrast, out-degree centralization values are consistently high and fall outside the ranges of the random graph values for all types of ties. This indicates that some actors position themselves as highly active or connected. While this may well reflect an effort to be influential or highly visible, these positions are not necessarily mirrored in how others nominate them (hence the low in-degree centralization values).

Further, short average path lengths for all graphs reveal an efficiently connected network, where most organizations are able to reach others through only a few intermediaries. However, only LP1 ("sharing material tools and resources"), LP3 ("implementing projects together"), and LP7 ("meeting in policy processes") have average path lengths with higher values than expected under random conditions. This implies more selective partnering in these domains, with certain actors favored over others. In the case of LP1, relatively more difficult resource sharing may be related to spatial proximity considerations, as only half of the actors are operating at a regional level, while the rest are locally-focused and potentially less mobile.

Finally, the moderate to high global clustering coefficients highlight variations in cohesion across interaction types, with some networks being more fragmented, and others being organized in tightly-knit subgroups. Most networks had higher than random global clustering coefficients. This is generally expected of social networks, due to social processes at play, such as preferential attachment or community formation (Robins 2015).

Overall, the network metrics depict a generally collaborative landscape, structurally non-random, and differentiated across interaction types, with both strong and weak ties, yet they also underscore the importance of analyzing specific relationship types in more detail.

Differentiation across networks Within this overall collaborative landscape, clear contrasts emerge across the twelve types of interactions. The knowledge and information exchange networks (LP4 and LP5) stand out with the largest number of ties and densities, highest in-degree centralization, lowest average path lengths and highest global clustering. This indicates that knowledge-related collaborations are more prevalent and structurally central than other types. While the clustering coefficients appear to be highest for LP4 and LP5, the comparison with random graphs reveals that these values are a statistical artefact of network density, otherwise not necessarily indicative of bonding capital in these networks. The high in-degree centralizations confirm that information and knowledge exchanges happen in a structure dominated by a few central actors, suggesting a hub-like structure in which many organizations rely on the same sources. However, the absence of correspondingly high clustering indicates that these exchanges do not form tightly interconnected, trust-based subgroups. At the same time, the low out-degree centralization values indicate that collaborations in the LP4 and LP5 networks might be perceived as sufficient and evenly distributed, as no organization is showing a stronger outward knowledge-seeking behavior than the others.

In contrast, other relationship types appear to be less frequent, less centralized and more dispersed. For instance, "applying for funding together" (LP2) and "reconciling differences in values and worldviews" (LP12) have the lowest densities and the highest out-degree centralization. This could indicate that, while such interactions are sparser and perhaps more strategic, a few organizations have a strong willingness to engage, or are highly motivated or positioned to take the lead in such interactions. The highest average path lengths in LP2, LP3 ("implementing projects together") also suggest that it may be most difficult to find partners for these types of interactions.

Generally, knowledge and information seem to flow rather efficiently through the network, although dominated by a few actors, in contrast with other emergent areas of collaboration where new efforts to engage are still necessary, but where leadership opportunities might be more evenly distributed. These descriptive differences motivate a closer examination of how different interaction types are structurally related to one another across the network.

Network correlations and ordering

The correlations in Table 3 further refine the findings above. Most values are relatively high, confirming that the actors have strong relationships spanning multiple types of interactions. Yet, some differentiation provides hypotheses about how various relationships might form. All pairwise comparisons were highly significant under QAP (*pqreq* = 0, *pleeq*[1] = 1). Among all networks, LP4 and LP5 exhibit the strongest correlation (0.80), pointing to a high reliability of the data collected, as information and knowledge exchange are expected to be intertwined in actors' interpretation.

LP4 and LP5 are also highly correlated with the networks of "sharing material resources and tools" (LP1) and of "exchanging informal advice" (LP6). The correlation with LP6 is unsurprising, as advice can be regarded as a

[1] *pqreq* refers to the proportion of draws greater than or equal to the observed statistic, i.e. in this case p(f(perm) >= f(d)): 0, while *pleeq* is the proportion of draws less than or equal to the observed statistic, i.e. in this case p(f(perm) <= f(d)): 1.

Table 3 Correlation matrix between the different networks

	LP1 Sharing materials resources and tools	LP2 Developing project applications	LP3 Implementing projects together	LP4 Exchanging information	LP5 Acquiring new knowledge	LP6 Exchanging informal advice	LP7 Meeting in policy processes/groups	LP8 Working to change policies	LP9 Setting up new collaborations	LP10 Pursuing similar strategies	LP11 Reflecting jointly on mission and goals	LP12 Jointly reconciling values and worldviews
LP1	NA	0.503	0.51	0.721	0.703	0.59	0.474	0.477	0.573	0.544	0.481	0.495
LP2	0.503	NA	0.727	0.527	0.502	0.562	0.459	0.483	0.568	0.447	0.538	0.514
LP3	0.51	0.727	NA	0.595	0.591	*0.612*	0.507	0.553	*0.633*	0.524	0.556	0.598
LP4	0.721	0.527	0.595	NA	**0.801**	0.703	*0.629*	0.512	*0.633*	0.583	0.57	0.529
LP5	0.703	0.502	0.591	**0.801**	NA	0.716	*0.622*	0.494	*0.625*	*0.613*	0.534	0.568
LP6	0.59	0.562	*0.612*	0.703	0.716	NA	*0.64*	0.575	*0.665*	*0.642*	*0.643*	*0.625*
LP7	0.474	0.459	0.507	*0.629*	*0.622*	*0.64*	NA	0.624	0.551	0.568	0.544	0.539
LP8	0.477	0.483	0.553	0.512	0.494	0.575	0.624	NA	*0.677*	0.572	0.596	0.596
LP9	0.573	0.568	*0.633*	*0.633*	*0.625*	*0.665*	0.551	*0.677*	NA	*0.604*	*0.652*	*0.612*
LP10	0.544	0.447	0.524	0.583	*0.613*	*0.642*	0.568	0.572	*0.604*	NA	*0.631*	*0.641*
LP11	0.481	0.538	0.556	0.57	0.534	*0.643*	0.544	0.596	*0.652*	*0.631*	NA	*0.642*
LP12	0.495	0.514	0.598	0.529	0.568	*0.625*	0.539	0.596	*0.612*	*0.641*	*0.642*	NA

All the correlations shown are highly significant under QAP (pqreq=0, pleeq=1). Bold indicates the strongest correlations, above 0.80, underline is for correlations above 0.70, and italics for correlations above 0.60

particular case of knowledge exchange. This finding is consistent with previous research showing that different types of social relationships among colleagues tend to be mutually embedded (Cross et al. 2001; Zagenczyk et al. 2013). The high correlation of LP4 and LP5 with LP1 is consistent with the hypothesis that proximity facilitates information and knowledge exchanges. However, the direction of this association cannot be inferred from these data.

Further, we note that information and knowledge exchanges are correlated with "meeting in policy forums" (LP7), but involvement in deeper joint strategic processes (LP10-12) is instead mostly correlated with the informal advice network (LP6). Similarly, joint project implementation (LP3) is moderately correlated with informal advice (LP6) and the setting up of new collaborations (LP9).

Figure 4 provides a visualization of the network correlations, based on a metric Multidimensional Scaling (MDS). The closer two data points in this figure, the more similar the respective networks are in terms of their correlation patterns with all other networks. The Goodness of Fit (GOF) values of 0.6602 and 0.6838 indicate that the 2D solution effectively captures the structure of the dataalthough some relationships remain unexplained by this representation alone.

To further integrate these findings, we complemented the analysis with a Guttman scaling procedure, similarly to Cross et al. (2001). This method reveals a hierarchical order of tie types, based on the systematic co-occurrence across dyads, which can be interpreted as reflecting how difficult it is to engage in those relationships. In a perfect Guttman scale, two organizations engaging in a "harder" type of relationship also engage in all the other embedded, "easier" ones (Fig. 5). Our results—with strong reproducibility (0.89) and moderate scalability (0.65) model fit—confirm that information and knowledge exchanges (LP4 and LP5) are at the lower end of the hierarchy, with LP3, LP12 and LP2 at the top. In other words, two organizations engaging in a project application relationship likely maintain all the other subordinated types of collaboration as well (but not vice versa). Importantly, this ordering captures patterns of structural embeddedness rather than mere co-occurrence among interaction types and does not imply specific relational mechanisms or motivations.

Taken together, our various analyses provide a coherent picture of how knowledge- and action-oriented interactions are structurally related within the network. Information and knowledge exchanges consistently co-occur with other types of collaborative relationships, suggesting their importance in enabling collective action. Sharing material resources, potentially mediated by proximity, may facilitate knowledge processes, while informal advice may be the entry point for joint engagement in strategic action and reflection.

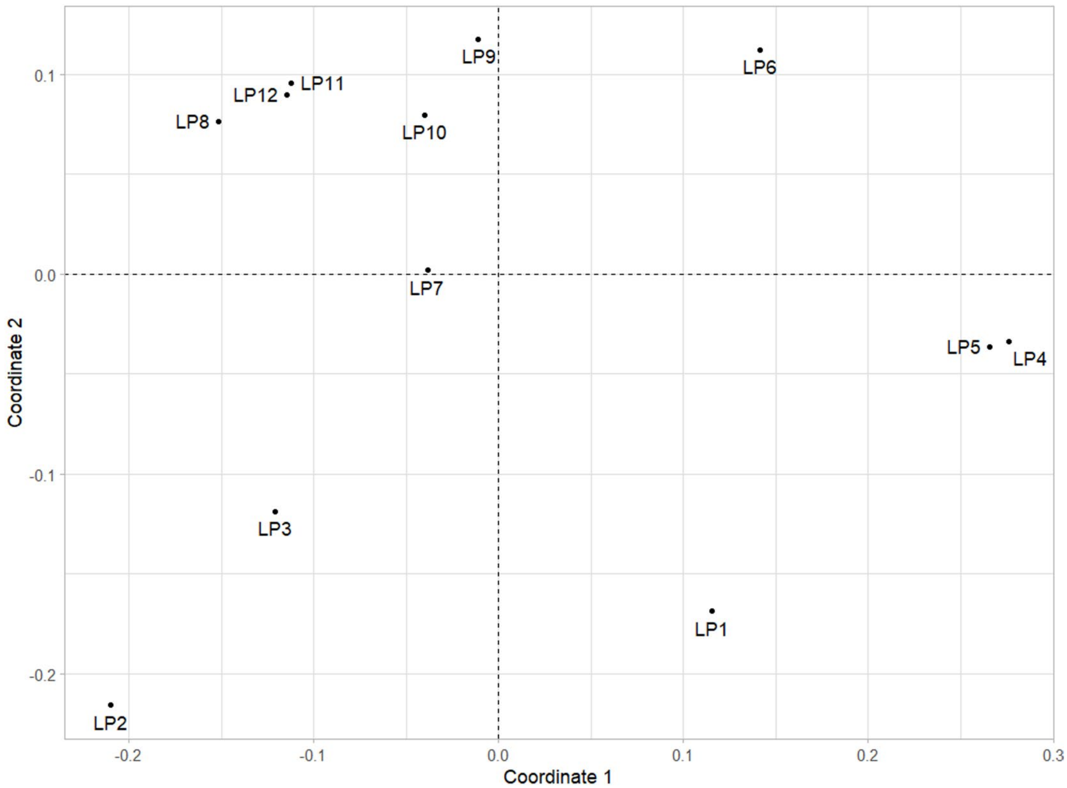

Fig. 4 Metric Multidimensional Scaling (MDS) of Network Correlation Values in Table 3. The relative distances between the networks are shown, based on their pairwise correlation values. GOF: 0.6602 and 0.6838

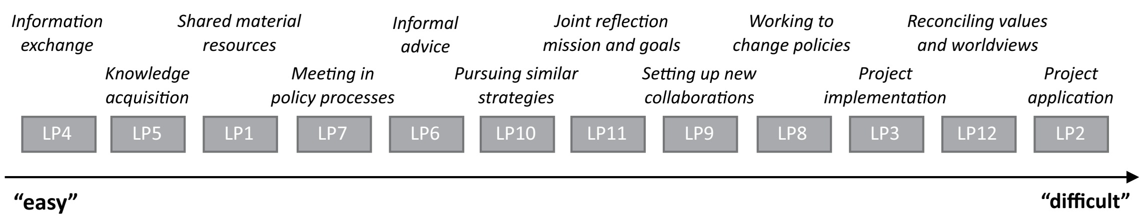

Fig. 5 Guttman scaling results: hierarchical order of 12 types of ties. The different types of interactions are ordered from the "easiest" to engage in to the "hardest", based on the presence of ties in the networks. Statistics: $N=992$, Total = 11,904, Guttman errors in optimal solution: 1334. Coefficient of Reproducibility (CR): 0.89; Coefficient of Scalability (CS): 0.65; Minimal Marginal Reproducibility (MMR): 0.68

Discussion

Our investigation into the knowledge system of Southern Transylvania's NGOs offers valuable insights into how knowledge and action intertwine in collaborative networks, some of which may be applicable to other contexts.

First, even within a dense network, organizations interact in different configurations depending on the type of relationships. Previous research highlights that collaboration involves the transfer and pooling of resources and skills that organizations do not have internally (Hardy et al. 2003), and that different organizational needs result in different network structures (Berardo 2014). The structural diversity in our data may reflect the dual need for both exploration (accessing diverse information) and exploitation (deep collaboration based on trust), supporting the view that collective action requires a balance of bonding and bridging ties (Bodin 2017; Bodin and Crona 2009, 2011).

Second, information and knowledge exchange networks displayed significantly different structures from other interaction types. These networks were highly centralized, indicating high bridging capital, which is typically associated with coordination problems (Berardo and Scholz 2010). This centralization may be related to the fact that only a subset of actors acquired expertise that others were missing, mainly technical, ecological and process-related (ESM S9). Based on our regional experience, actors with such specialized knowledge likely function as brokers across

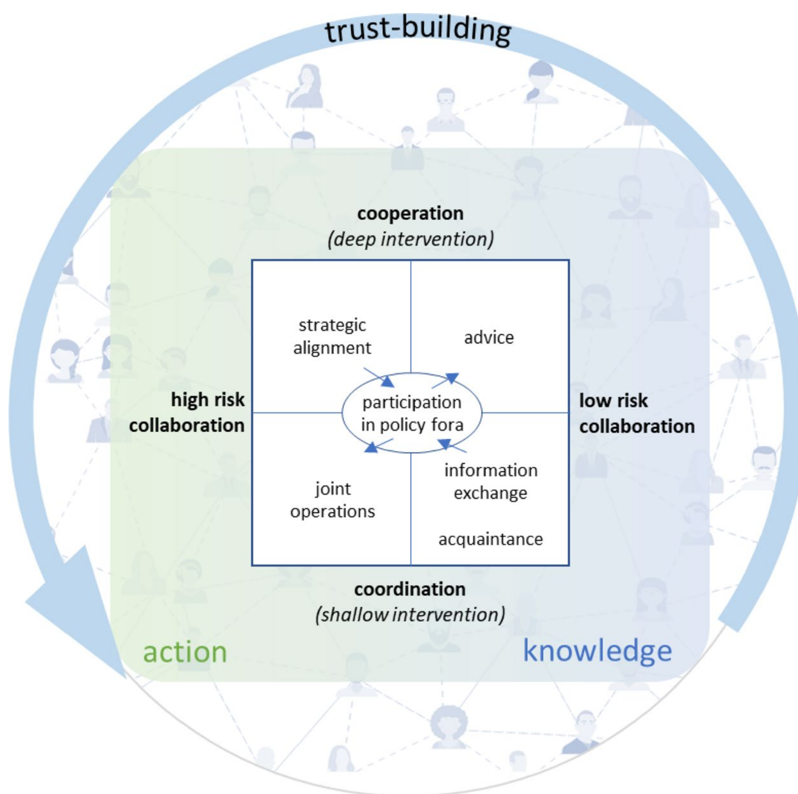

Fig. 6 The interplay of knowledge and action in collaborative networks: A working hypothesis. The small arrows in the middle indicate that participation in policy fora acts as an enabler of trust-building and of transitioning collaboration from low- to high-risk and from coordination to cooperation

structural holes (Berardo 2014; Burt 1992). While centralization may enhance the efficiency of knowledge search, an over-reliance on a few actors introduces vulnerabilities and reduces opportunities for innovation (see discussion in Bodin and Crona 2009). Moreover, the high correlations between knowledge-related and advice networks suggest that knowledge flows are embedded in both cognitive and relational structures, where trust-based mechanisms, such as those demanded by informal advice, influence knowledge acquisition. At the same time, the relational aspect also risks rendering the network susceptible to misinformation or the reinforcement of existing biases (Ejaz et al. 2024).

Third, a hierarchical structure of engagement emerges across collaboration types. In the MDS map, we noted that the *y*-axis alignment reproduced the hierarchy of leverage points for intervening in a system, with interactions related to "deeper" system interventions at the top and those related to "shallow" ones at the bottom (Abson et al. 2017), but also with notable exceptions such as those illustrated by LP6 and LP9. Meanwhile, the *x*-axis roughly mirrored the Guttman ordering (from right to left), where information and knowledge exchanges appear as the most accessible interactions, while strategic alignment and project implementation are among the most demanding. Proximity and homophily appear to shape this hierarchy, as illustrated by the overlap between LP1 and LP4 and LP5, which likely reflects co-location and frequent face-to-face interaction. Where knowledge ties extend across distances, these may be linked to shared thematic focuses and the search for expertise complementarity, as resulting from the additional survey data (ESM S9). Taken together, these patterns offer plausible hypotheses about how knowledge-action networks form and progress towards action.

One possible collaboration trajectory is that collective action often begins with initially shallow quests for knowledge, information and easily accessible resources (such as physical space, materials or tools), the sharing of which is low cost and entails low risks for the organizations. These relationships may co-occur with meetings in policy forums (LP7) and they resemble "coordination", as discussed previously (see also Yi 2018). As trust builds, interactions enter the sphere of "cooperation", and also move towards activities where higher risks are at stake (e.g., financial, reputational). Within the context of climate adaptation, Ingold (2017) could also establish that, as a network is being formed, the frequency of information relations is higher than that of collaboration interactions. Further, our findings suggest that a strategic alignment of priorities for policy intervention, as well as of mission and goals (LP8-LP11) might precede involvement in joint operations (i.e., projects), as shown by LP2 and LP3 being among the most "difficult" areas of collaboration according to the Guttman ordering. Figure 6 captures this hypothesis and is meant as an interpretative device, rather than a model of causal sequencing, to highlight how different forms of collaboration may co-occur and potentially evolve as relationships become more embedded.

The observed patterns also speak to the debates surrounding the risk hypothesis reviewed in Sect. "Relevant concepts and insights from social network analysis". While our findings do not test these propositions directly, we offer a possible resolution, by disaggregating between the level of collaborative risk, the difficulty of the joint action (level of intervention in the system) and trust. As Fig. 6 depicts, both high-risk and low-risk collaborations may involve coordination or cooperation structures—but for different reasons. High-risk situations (e.g., financial or reputational exposure) call for bonding first, and then expand with bridging ties, with trust as a prerequisite even for seemingly simple operational collaborations. In contrast, in low-risk situations collaborations may begin through bridging ties and then evolve towards bonding (as seen in the advice network). Trust-building then, is a process that starts in the lower right quadrant with easy, transactional information sharing, and gradually creates space for the stronger, cooperation-type interactions, moving towards the higher-risk activities of joint strategizing and, finally, operational coordination (lower left). In our context, the lower densities in the LP2 and LP3 networks may reflect competition for scarce financial resources, leading to high selectivity of project partners, but also illustrate that trust is still not fully consolidated in the network.

We also note that knowledge processes should not be understood as exclusively associated with low-risk collaborations. While LP4 and LP5 frame knowledge exchanges in linear, instrumental terms, according to a transfer and translate model (van Kerkhoff and Lebel 2006), the additional survey demonstrates that more complex, co-productive knowledge processes underpin decision-making and strategic action (Bandola-Gill et al. 2023; West et al. 2019). Against this backdrop, meeting in policy fora (LP7) appears to function as a transitional space (inflection point), where trust is built incrementally, collaborations shift from low- to high-risk domains, and transactional knowledge agency is transformed into co-productive knowledge-action agency. Recognizing this dynamic can guide efforts to strengthen collaborative capacity and build more resilient knowledge-action systems.

Finally, our findings on tie embeddedness can also be reintegrated into broader sustainability science debates on linking knowledge and action. Wyborn (2015), building on Jasanoff's (2010) co-production framework, asserts that material, cognitive, social and normative capacities must be nurtured together to enable effective collective action[2]. In our case, relationships reinforcing mutual material capacities (LP1) overlap with those fostering cognitive capacities (LP4, LP5), while normative capacities for reshaping the social environment (associated with high-leverage networks LP9-12) appear grounded in informal advice relationships (LP6). This supports the idea that these various capacities are not activated in isolation, but that they indeed require simultaneous embedding within a functioning knowledge system.

Taken together, these patterns provide an answer to our research question, showing that knowledge- and action-oriented relationships are structurally distinct, yet hierarchically ordered and interdependent. This provides empirical support that strengthening knowledge systems for sustainability transformations requires moving beyond knowledge exchange alone towards enabling the relational infrastructure that co-production scholars have been advocating for (Jager et al. 2020; Maas et al. 2022; West et al. 2019; Wyborn et al. 2019).

Limitations and future research

In considering our proposed model of how knowledge systems for collective action operate, a few limitations need to be noted. First, the case-based nature of our findings limits generalizations. Beyond validating our results, future studies might explore the emergent hypotheses more systematically, for instance by assessing different types of network brokerage and knowledge to understand the nuanced roles organizations play in facilitating resource flows (Becker and Bodin 2022; Gould and Fernandez 1989; Kiwanuka et al. 2020; Ward et al. 2009). Second, while our findings might be interpreted as a potential temporal sequence in the evolution of collaboration, the cross-sectional nature of our data restricts further analyses. In particular, the two-dimensional reading of collaboration that we propose in the discussion represents an exploratory and dynamic reinterpretation of the risk hypothesis, which future work should examine more systematically, including through longitudinal network studies and comparative cases. Similarly, examining *within*-initiative/organization collaborations could provide a richer depiction of what drives interorganizational collaborative dynamics. Third, a deeper examination of the role of proximity and homophily might be fruitful, yet moving beyond

[2] Material capacities refer to tangible resources and funding that sustain relationships between actors, cognitive capacities involve processes of generating knowledge that is salient, credible and legitimate (Cash et al. 2002), social capacities relate to building collaboration through communication, mediation and translation; and normative capacities pertain to underlying shared values and motivations.

node attribute analysis to considering the flows of influence in a network is also important (Ward et al. 2011). Research on knowledge flows could be linked to collective action impacts using frameworks such as the Advocacy Coalition Framework (Weible 2006) or the Ecology of Games (Lubell 2013). This could illuminate the dynamics of coalition-building and policy influence across multiple fora (Hedlund et al. 2021), but also further explain the mediating role of policy participation in linking knowledge to action. Lastly, while our results are strongly triangulated, the individual network metrics do not account for conditional dependencies among ties and were therefore interpreted with caution, primarily to contextualize the core correlational analyses. Future studies could address this more formally, and would also benefit from using more objective interaction metrics, rather than self-reported assessments.

Conclusion

Our study highlights the importance of a multifaceted approach to understanding knowledge systems and their role in collective action for sustainability. By examining multiple types of interactions in a network of sustainability initiatives from Romania, we demonstrate that knowledge and information processes are pivotal in creating collaborations and kick-starting knowledge-action networks. However, informal relationships are likely the catalyst for strategic collective action, while building trust via repeated interactions is key in moving from shallow to deeper system interventions and from lower- to higher-risk, more costly, activities.

Actors' proximity, as well as homogeneity of interests potentially provides the common ground for initial interactions, while relevant policy-making fora create opportunities for bringing actors together. However, these initial connections need to be sustained long-term, so as to foster an environment where other types of relationships can develop. This suggests that enhancing knowledge-action networks cannot focus on knowledge exchange alone, rather the relational infrastructure that enables deeper collaboration must be cultivated deliberately and over time.

While our findings need to be validated in other contexts, a few general implications for practice and policy can be derived. On the practice side, visionary network organizers should be encouraged to assume brokerage roles on other aspects beyond just knowledge and information, and to intentionally design deep collaborations by: nurturing informal connections, creating spaces for reflection and joint strategic planning, actively facilitating project opportunities for others, promoting others to arenas of political influence etc. At the other end, policymakers could implement initiatives that support such practices. For instance, programs could be designed to support co-working environments and encourage the use of shared physical spaces by NGOs. By bridging practice and policy, future research and action can better harness the potential of knowledge systems to drive collective efforts toward transformative societal and environmental outcomes.

Appendix

Glossary of network measures used in Table 2

- Number of ties—the number of reported collaborative links between the 32 nodes;
- Density—the proportion of observed edges relatively to all possible edges;
- Connectedness—this is the fraction of all dyads (pairs of vertices) that have a path between them (undirected);
- Degree centralization—this is the normalized sum of deviation of degrees from the most popular node. A high centralization value means that a few actors are highly popular;

  – First measure: normalized to the highest degree / variance of degrees;
  – Second = general index Freeman: normalized to the theoretical maximum centralization (g-1)*(g-2);

- Average path length (calculated here as directed, not considering weights)—average of the length of the shortest path between any two vertices;
- Global clustering coefficient / transitivity (calculated here as direct ratio of triangles to triplets)—probability that a node i connected to j also connects to k in its neighborhood.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11625-026-01865-1.

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Author contributions Cristina I. Apetrei: Conceptualization, Methodology, Software, Formal (data) analysis, Writing—original draft, Writ-

ing—review & editing. Nicolas Jager: Methodology, Writing—review & editing, Supervision.
Daniel Lang: Methodology, Writing—review & editing, Supervision, Project Funding.

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Data availability The data set pertaining to the analyses is available upon request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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