

Resilience Assessment of Laboratory Networks: A Multi-Indicator Approach

Oana Daniela BUGAN*

National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania

*Corresponding author, oana.bugan@upb.ro

Sorin Cristian IONESCU

National University of Science and Technology POLITEHNICA Bucharest, Bucharest, Romania

sc.ionescu@gmail.com

Abstract. *The paper proposes a multi-dimensional analysis to evaluate the performance and resilience of eight Romanian research laboratory networks, regarded as complex socio-technical ecosystems. Graph theory, network performance analysis and agent-based modeling were applied, while the use of structural, operational, performance and collaborative indicators helped assess the behavior of different networks typologies under disruptive conditions. Data was derived from publicly available information and inputs and estimations from researchers activating in these laboratory networks. Our findings show that resilience, adaptability and robustness depend not only on the technical infrastructure, but also on the collaboration mechanisms, active knowledge transfers, and distributed governance mechanisms. The proposed approach offers a richer insight into the complexity of research laboratory networks, offering decision-makers tools for establishing adaptable and robust systems.*

Keywords: Research networks, Laboratory networks, Collaborative networks, Network analysis.

Introduction

Industry 4.0 uses complex technologies and digital solutions for the transfer of knowledge, information and helping the co-creation and co-innovation process. The constant dynamic of the research environment due to rapid technological developments has forced research laboratories to shift from isolated entities to seeking connections to other research and innovation facilities, to open knowledge transfer and open science that help advancing solutions needed for the complex problems the world is facing. Such technological complexity requires large capabilities that are hard to acquire within a single research facility.

As digital solutions emerged, collaborative platforms are utilized in the research process, bringing together different entities relying on each other's resources, facilities and capabilities, generating laboratory networks. But the use of such platforms needs a solid collaborative governance system with harmonized procedures and methodologies that integrate socio-technical, structural, operational, organizational and collaborative aspects of these ecosystems. The lack of a holistic approach to research networks, integrating both management and complex network theory (M. E. J. Newman, 2003) increases vulnerability and reduces adaptability of the collaborative effort.

Relying on centralized coordination models leads to failure under stress conditions such as demand surges or partner reconfiguration (Jia et al., 2015; Zhang et al., 2021) while adopting network configurations increase resilience and robustness under disruptive conditions (Yao, 2014).

The analysis of existing literature show that most approaches are oriented towards standardization and conformity (International Organization for Standardization, n.d.) considering

the architectural, technical or structural indicators of networks, or towards energy efficiency, safety and automation in the case of smart labs (I2SL, n.d.). But these approaches provide a limited insight of collaborative research networks, not considering all aspects of a network and integrating its socio-cultural dimension or the governance aspects.

To address this gap, we have analyzed eight laboratory networks in Romania, proposing a multi-indicator evaluation that cover all aspects of a complex multi-dimensional research network. We analyzed the structural properties such as connectivity, modularity and centrality that influence robustness and system behavior (Barabási & Pósfai, 2017; M. Newman, 2010), the interaction between technical infrastructure and social processes (Geels, 2004; Trist, 1981), collaborative capabilities and knowledge transfer (Allee, 2008; Camarinha-Matos & Afsarmanesh, 2008; Nof, 2017) and apply agent based modelling (ABM) to observe the networks' responses to disruptive conditions (Bonabeau, 2002; Thiele & Grimm, 2010).

The study aims to answer three research questions:

- RQ1 How do different laboratory network structures influence robustness and resilience under disruptive conditions?
- RQ2 How does the balance between the tangible and intangible flows influence laboratory network resilience?
- RQ3 Which structural, operational and collaborative indicators help differentiate between high-performing laboratory networks and vulnerable ones?

Methodology

The multi-indicator approach used evaluates the structure, performance and resilience of eight Romanian research laboratory networks, state and private owned, with different architectural typology – centralized, distributed and hybrid and activating in different fields.

The data was derived from analyzing public information (domain, staff, impact, governance, international projects), inputs from researchers activating in these labs (partners, role in the network and type of network, digital maturity, equipment/infrastructure, patents, etc.) and estimations by the same researchers of data considered private by the laboratories (interoperability, intangible flows, revenue, etc.).

The study focused on comparing lab networks, evaluating performance, resilience and analyzing operational behavior.

Network structural analysis (RQ1)

Each laboratory network was modelled as a graph where nodes represent other labs or key partners, and edges represent the flows between the nodes (collaboration, knowledge sharing).

The eight networks have centralized, distributed or hybrid topology and their structural indicators like modularity, clustering, betweenness, and density helped characterize each configuration and the responses to stress conditions. To answer our research questions, we compare the results of networks with the same structural configuration to see if they behave similarly, and if we can derive a hierarchy based on network typology in terms of adaptability, resilience and performance. We depart from the generally accepted properties of these different types of networks:

- centralized networks have a strong control over and governance, but high dependency on the central node;
- distributed networks have high adaptability and are decentralized;
- hybrid networks combine centralized governance with decentralized collaboration.

Socio-technical and Collaborative Performance Assessment (RQ2)

The analysis of socio-technical and collaborative dimensions captures how the laboratories function as embedded actors in the network ecosystem.

The tangible flows (e.g., services – transferred or redirected tasks, equipment sharing, infrastructure usage) and the intangible flows (e.g., knowledge exchange, trust, interoperability readiness) were grouped into Tangible Value Flow Index (TVFI) and Intangible Value Flow Index (IVFI), and analyzed through the Value Conversion Efficiency (VCE) (Camarinha-Matos & Afsarmanesh, 2008) indicator that measures how labs transform resources and collaboration into results. The digitalization level and automation integration were analyzed through the Operational Integration Index (Olx).

Collaborative maturity and operational performance were analyzed through the CCT-Nof indicator (Nof, 2017).

Resilience and Adaptability Assessment (RQ3)

To analyze the resilience of the networks and their adaptability, four disruptive or stress scenarios were used to best capture all aspects of collaboration:

- Demand shock – a four times increased demand of sample analysis;
- Blockage – the failure of a central node;
- New partner – the integration of a new partner laboratory into the network;
- Interoperability – the digital connectivity, knowledge and data exchange.

All parameters were normalized to the interval [0,1] to ensure comparability of all network configurations – centralized, distributed and hybrid. Indicators such as successful rerouting rate, mean time to recovery (MTTR), operational autonomy and viability capture the disruption effects and post-shock recovery behavior.

The four scenarios were used as comparative tests and not predictive models, that show the differences between high-performing networks and vulnerable ones in terms of resilience and adaptability.

All computations were performed in Python, using NetworkX and Pandas for networks reconstruction, normalization and data processing, and Matplotlib for comparative visualizations. Structural metrics were also computed through NetworkX and using Gephi for visualization. The behaviour under the four disruptive scenarios was analyzed using agent-based modeling (ABM) performed in Python. These different approaches allow a complete evaluation of the network structure, collaboration and performance.

Case study – 8 Laboratory Networks

The eight analyzed laboratories (labeled as L1, L2, ... L8) illustrate diverse fields of research, network typology and system governance. We investigated different dimensions during the study to help us draw the indicators needed for analysis, only the most representatives being illustrated in Table 1.

The different number of network partners, digitalization level and governance type allow us to draw conclusions regarding resilience and adaptability but also to capture the behaviour and establish a hierarchy.

Table 1. Structural and organizational characteristics of the 8 laboratory networks

Network	Domain	Estimated staff	Estimated active partners	Role in the network	Impact	Type of network	Digital maturity	Inter-operability	Governance type
L1	Water quality monitoring	40	5	Central node	Ensures critical compliance with quality guidelines	Centralized	Medium-high	Medium	Private
L2	Medical analysis	1,200	40	Main provider hub	Provides large-scale diagnostic services and health data interoperability	Hybrid	High	Medium	Private
L3	Telecommunication testing	50	25	Major hub	Validates telecommunication protocols in field conditions	Distributed	High	High	Private
L4	Forensics	300	20	Central node	Supports judicial processes via expert reports	Centralized	Medium	Controlled	State
L5	Physical chemistry & materials	150	20	Central node	Generates reference data for material science and chemical calibration	Centralized	Medium	High	State
L6	Metrology & standards	250	15	Central node	Provides traceability and metrological standards	Centralized	Medium	High	State
L7	Industrial chemistry	200	30	Thematic hub	Develops applied chemical processes and industrial solutions	Hybrid	Medium	High	Private
L8	Environmental testing	180	25	Central node	Monitors environmental pollutants and supports regulatory compliance	Centralized	Medium	Medium	Private

Source: Authors' own research.

Results and discussions

In Table 2 we have the results of structural, collaborative and socio-technical indicators derived from the data set we collected.

Clustering shows the tendency of a laboratory to form connected groups, and how connected they are to each other, while *density* indicates how many connections form between the labs of a group relative to the number of possible connections that could form. *Modularity* shows how the network is divided into groups with more connections within groups than between them. *Betweenness* indicates the role of a lab in the network, whether it is an intermediary or facilitates connections across the network.

The Olx reflects the level of digitalization and interconnectivity of the network. The intangible brokerage measures the degree of knowledge, information and data sharing of a lab (node), while the Social vulnerability shows how vulnerable or sensitive the network is when facing disruptive conditions such as failure of a lab (node).

Table 2. Structural, collaborative and socio-technical indicators of the 8 laboratory networks

Network	Clustering	Density	Modularity	Betweenness	Collaborative resilience	Olx	Intangible brokerage	Social vulnerability
L1	0.5	0.4	0.5	0.28	0.88	0.69	0.187	0.382
L2	0.55	0.45	0.45	0.28	0.93	0.805	0.264	0.344
L3	0.5	0.35	0.4	0.225	0.83	0.79	0.212	0.35
L4	0.35	0.25	0.35	0.175	0.78	0.605	0.097	0.392
L5	0.35	0.25	0.35	0.175	0.78	0.725	0.156	0.368
L6	0.25	0.15	0.25	0.3	0.83	0.555	0.25	0.494
L7	0.4	0.3	0.4	0.215	0.88	0.78	0.215	0.362
L8	0.35	0.25	0.35	0.175	0.85	0.645	0.117	0.384

Source: Authors' own research.

L2 stands out as the most resilient and integrated network. It has high indicator values showing digital maturity and a high collaborative characteristic. The low social vulnerability shows that the network is resilient and adaptive. L7 has good connectivity, digital maturity and shows resilience but with low interconnectivity.

L1 is a central node with high clustering value and betweenness. It functions as a central hub in a well-connected network, and shows collaborative resilience, but moderate digitalization level. It can perform under disruptive conditions, but the low brokerage indicates it has an operational role, rather than innovative.

L3 has strong local connectivity and digital maturity, and its distributed nature allows for flexibility and adaptability, and the failure of the central hub would not disrupt the network, as the labs (nodes) do not play a role in connecting other labs within the network. L8 has low modularity and limited brokerage and digital maturity. However, it displays a relatively strong resilience.

L4 is centralized and less resilient and flexible. It has limited brokerage capability which indicates a less collaborative characteristic and reduced adaptability. L5 shares similar characteristics with L4 with limited resilience, low sharing capabilities and socio-technical robustness. L6 has low clustering and connectivity which leads to the weakest resilience and high social vulnerability, leaving it as the weakest network in the analysis set.

This analysis shows that network typology influences resilience and performance. The hybrid networks perform best and show adaptability under stress, while the centralized networks are robust but less adaptable and vulnerable. Distributed networks show good levels of interoperability but less strong resilience.

Figure 1 illustrates the CCT-Nof profiles for the eight networks, in terms of six collaborative indicators: *dynamic reconfiguration* (adaptability under stress conditions), *shared context*, *plug&play capability* (adding or removing labs in the network without disruption), *learning*, *performance alignment* (same objectives across the network) and *conflict management*.

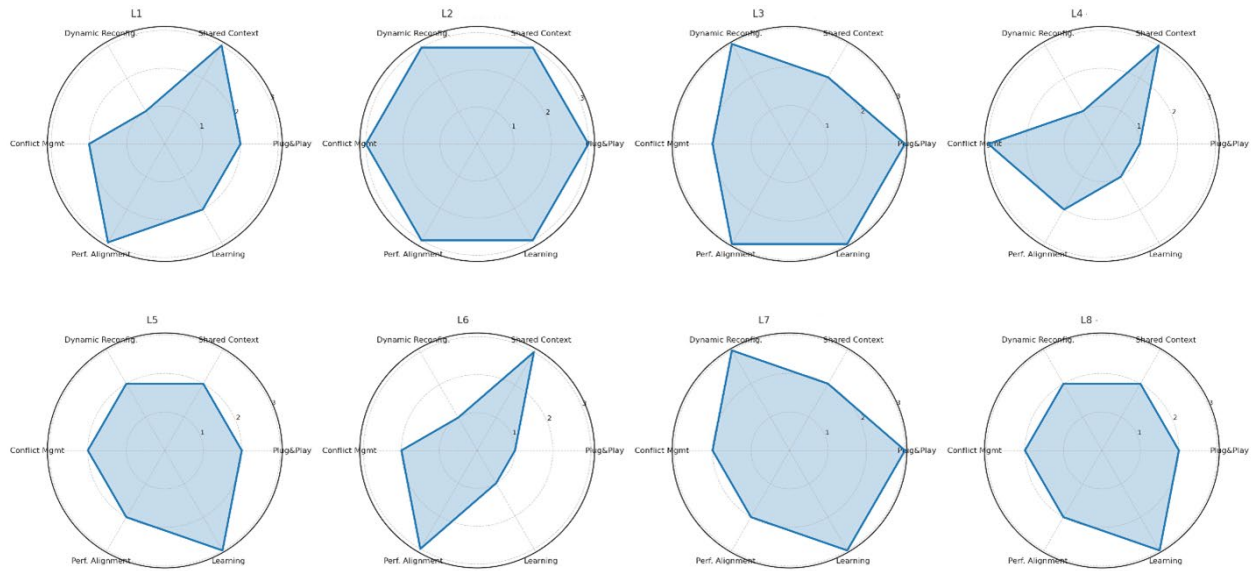


Figure 1. CCT-Nof profiles of the eight laboratory networks

Source: Authors' own research.

L2 and L7 display the most balanced profiles with high values of all six indicators, suggesting strong integration capabilities, resilience and maturity.

L3 and L1 show adaptability and learning capacity, but having low values for shared context and conflict management suggests poor governance. L5 and L8 have moderate scores across all six indicators, suggesting fewer collaborative capabilities.

L6 and L4 show the lowest scores, demonstrating vulnerable networks under stress conditions and less balanced characteristics.

Figure 2 shows the socio-technical indicators of the networks and the capability to transform tangible and intangible flows into productive results.

Figure 2 illustrates the socio-technical indicators for our networks.

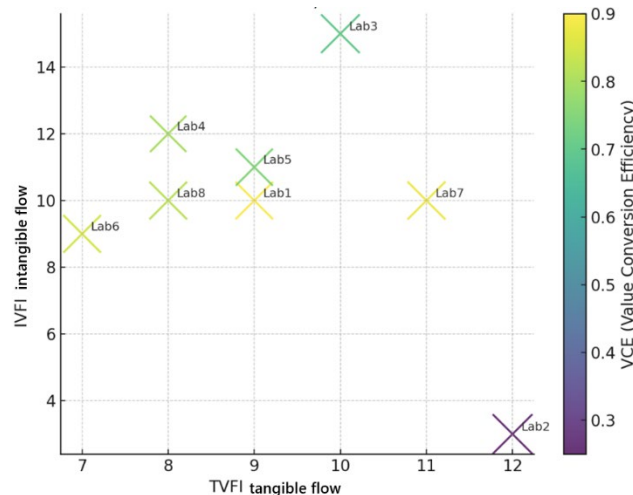


Figure 2. Socio-technical indicators of the eight laboratory networks

Source: Authors' own research.

L3 indicates strong intangible value flows, with high levels of knowledge exchange and collaborative capability. L7 network is efficient but has a moderate intangible flow index, showing a weaker interoperability. L1 is a balanced network with medium flow indexes in both tangible and intangible resources.

L4, L5 and L8 show collaboration orientation but minimum efficiency, not managing to convert the knowledge exchange into valuable results.

L5 and L7 have balanced results with high efficiency and capability of transforming resources into results.

L6 is positioned lower on both axes showing limited technical and social integration. L2 has the lowest intangible flow index and value conversion efficiency, suggesting a minimal collaborative aspect, each lab (node) relying on its own structure rather than working with others. It uses a lot of resources but does not have impactful results.

The analysis demonstrates that networks with balanced socio-technical systems perform more efficiently and display stronger resilience, adaptability and robustness under disruptive conditions, while networks dominated by tangible flows have weak collaboration and less resilience.

Figure 3 illustrates operational and collaborative performance, using the Camarinha-Matos&Abreu framework. The indicators observed were: *Cost*, *Utilization Rate* (UR: how much the technical and human resources are used), *Task Responsiveness* (TR: the speed of response), *Resource Collaboration Index* (RCI: the rate of sharing resources across the network), *Rerouting Rate* (RR: the rate of transferred or redirected tasks), *Interoperability* (IOP: the degree of collaboration), *Knowledge Sharing* (KSH: effective knowledge and information exchange), and *Connectivity* (how linked the laboratories of the network are).

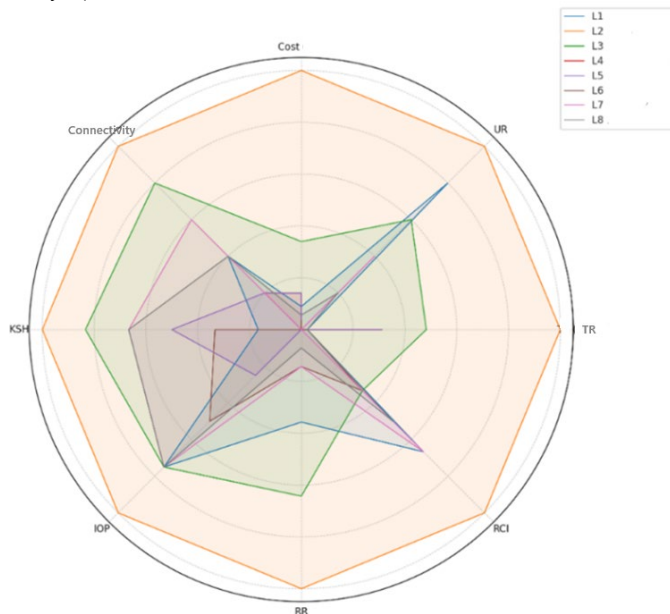


Figure 3. Operational and collaborative indicators of the eight laboratory networks

Source: Authors' own research.

The results show that L2 is the most balanced network with high performance in terms of operational and collaborative efficiency. It demonstrates a mature network with strong

interoperability, high resource utilization, well-established governing mechanisms and resource sharing. L3 demonstrates high connectivity and strong collaboration and interoperability, but less adaptability.

L1 and L7 have moderate connectivity and limited learning capabilities and adaptability. L4, L5 and L8 have moderate scores showing weak collaboration, limited flexibility and responsiveness but medium interoperability.

L6 is the weakest and most imbalanced network with very low connectivity, adaptability and poor governance.

The analysis reflects how flexibility, interoperability and knowledge sharing directly impact resilience and collaborative performance.

Figure 4 illustrates network performance under stress conditions within the four disruptive scenarios we simulated. The analyzed indicators were *Successful rerouting* (transferring or redirecting tasks), *Mean time to recovery* (MTTR: the time required for the network to recover from the disruption), *Timeliness* (reaction time to completing tasks), *Viability* (ability to remain functional over time), *Autonomy* (the independence of a node), *Severity index* (vulnerability to disruptions or stress) and *Degree of optimization* (DOP_optim: efficiency under stress).

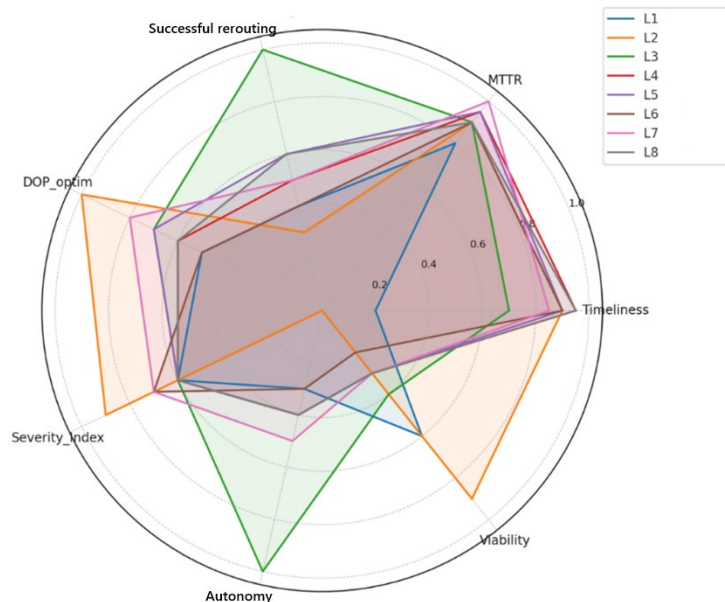


Figure 4. Performance under stress scenarios of the eight laboratory networks

Source: Authors' own research.

L3 is the most resilient network, very successful in rerouting and has good results for almost all indicators. It has high adaptability and maintains functionality and efficiency under disruptive conditions, but lower viability and timeliness which do not affect the rerouting capability and functionality.

L2 has good scores in timeliness, viability and DOP_optim, suggesting high operability, but show slow autonomy and rerouting which indicate low flexibility and reliance on external resources.

L5, L6 and L7 show moderate resilience, strong capabilities for recovery and MTTR. They can respond quickly but are not very adaptive or autonomous.

L1 shows good MTTR but weak viability and successful rerouting, suggesting weak adaptability and resilience. L4 is the most vulnerable network, scoring lowest across all indicators and showing weak adaptability and resilience.

L8 shows a balanced network with average performance and medium scores. It has good MTTR and Timeliness but low rerouting and autonomy.

Resilient networks have strong connectivity, high operational capabilities and good collaboration indicators. Vulnerable networks have limited adaptability, are less flexible and highly dependent on the central node (lab).

Figure 5 illustrates the response under disruptive conditions and recovery rate, complementary to the previous analysis.

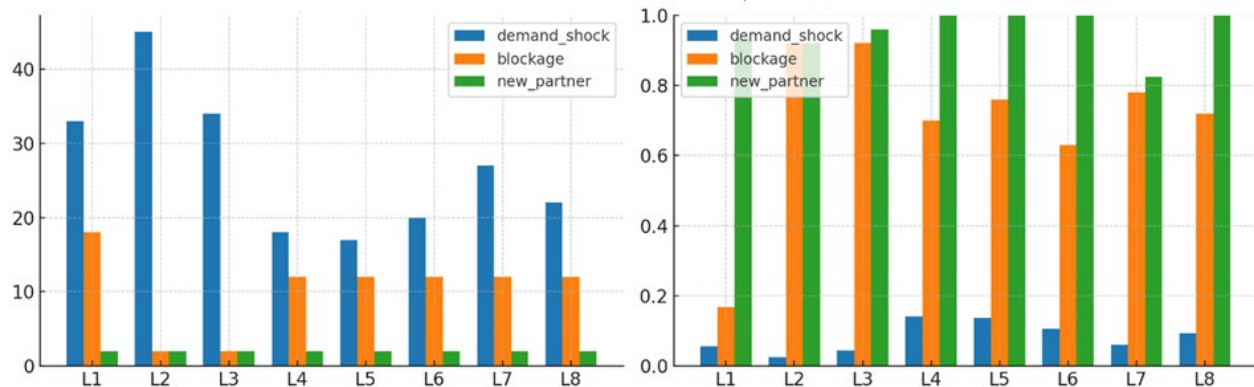


Figure 5. Recovery performance of the eight laboratory networks

Source: Authors' own research.

For the demand shock scenario L2 and L3 demonstrate a strong capacity to absorb shock due to automation and digitalization readiness. L1 and L7 reacted quickly on short-term disruptive conditions showing elasticity, while L4, L5 and L6 proved most vulnerable.

For the blockage of a central node (lab), L2 and L3 demonstrated near-instant recovery capabilities due to high automatization characteristics. L1 recovered quickly relying on the manual input which is less robust. L7 and L8 score medium with moderate delays. L4, L5 and L6 suffered major disruptions showing vulnerability and high dependency on the central hub.

For the new partner scenario, most networks show capacity to redistribute and good elasticity. L4 shows the barrier represented by the procedural constraints of a centralized and controlled network. L6 shows structural rigidity with low adaptability.

Robust networks show ability to perform under stress conditions and vulnerable ones show less flexibility and reliance on external support. The rerouting capacity and short recovery time indicate good adaptability, while high dependency of centralized networks indicates vulnerability and fragility.

Conclusion

The scenarios help identify patterns of different laboratory network typology. Networks with the same typology tend to behave similarly, although their performance and resilience are quite different.

Centralized networks show lower adaptability, are more vulnerable to disruptions and have high dependency on the central hub. Distributed networks are highly adaptive and robust, showing

connectivity, autonomy and less dependence. The hybrid networks show the best balance between efficiency and adaptability, illustrating resilience and flexibility.

Our findings show that resilience, adaptability and robustness are not only dependent on the technical infrastructure, but also on the collaboration mechanisms, active knowledge transfer, and collaborative governance mechanisms. To assess the performance of the networks multiple indicators must be analyzed. The multi-indicator approach we used in our analysis evaluates the laboratory networks under all aspects, considering them being complex structural, operational and socio-technical ecosystems.

The research proves that different laboratory network typologies influence performance, the socio-technical balance is important for network resilience and multi-dimensional indicators are necessary to help differentiate between high-performing laboratory networks and vulnerable ones.

From a practical perspective, it is important to improve knowledge sharing mechanisms, interoperability and distributed governance to help enhance the performance, not only the technical infrastructure. The proposed approach offers a richer insight into the operational and collaborative dimensions of research laboratory networks, offering decision-makers tools for establishing collaborative governance mechanisms and distributed robust systems.

While we believe our results help broaden the understanding of performant laboratory networks, our investigation has limitations. A key limitation relates to our focus on Romanian laboratory networks only, and further work could expand the research to the broader community of laboratory networks. Another limitation comes from the fact that some data was estimated by expert researchers, which may be subject to bias due to potential subjectivity.

References

- Allee, V. (2008). Value network analysis and value conversion of tangible and intangible assets. *Journal of Intellectual Capital*, 9, 5–24. <https://doi.org/10.1108/14691930810845777>
- Barabási, A.-L., & Pósfai, M. (2017). *Network science*. Cambridge University Press.
- Bonabeau, E. (2002). *Agent-based modeling: Methods and techniques for simulating human systems*. www.pnas.org/cgi/doi/10.1073/pnas.082080899
- Camarinha-Matos, L., & Afsarmanesh, H. (2008). *Collaborative Networks: Reference Modeling* (p. 336). <https://doi.org/10.1007/978-0-387-79426-6>
- Geels, F. W. (2004). From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory. *Research Policy*, 33(6), 897–920. <https://doi.org/10.1016/j.respol.2004.01.015>
- I2SL. (n.d.). *International Institute for Sustainable Laboratories (I2SL)*. Retrieved April 24, 2025, from <https://smartlabs.i2sl.org/case-studies.html>
- International Organization for Standardization. (n.d.). *ISO Standards Catalogue*. Retrieved October 16, 2025, from <https://www.iso.org/standards.html>
- Jia, T., Liu, Y.-Y., Csóka, E., Pósfai, M., Slotine, J.-J., & Barabási, A.-L. (2015). *Emergence of bimodality in controlling complex networks*. <https://doi.org/10.1038/ncomms3002>
- Newman, M. (2010). *Networks : an introduction*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199206650.001.0001>

- Newman, M. E. J. (2003). The Structure and Function of Complex Networks. *SIAM Review*, 45(2), 167–256. <https://doi.org/10.1137/S00361445034248>
- Nof, S. Y. (2017). Collaborative Control Theory and Decision Support Systems. *Computer Science Journal of Moldova*, 25(2), 115–144.
- Thiele, J. C., & Grimm, V. (2010). NetLogo meets R: Linking agent-based models with a toolbox for their analysis. *Environmental Modelling and Software*, 25(8), 972–974. <https://doi.org/10.1016/j.envsoft.2010.02.008>
- Trist, E. (1981). *Evolution_of_socio_technical_systems*.
- Yao, J. (2014). *Understanding institutional collaboration networks: Effects of collaboration on research impact and productivity*. University of Southampton.
- Zhang, D., Guo, C., Zhang, Z., & Long, G. (2021). Assessing the Structural Vulnerability of Online Social Networks in Empirical Data. *Frontiers in Physics*, 9. <https://doi.org/10.3389/fphy.2021.733224>