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Enhancing causal loop diagram analysis through network measures

A comprehensive framework and an illustrative case study on maternal and child health systems in Tanzania and Zambia

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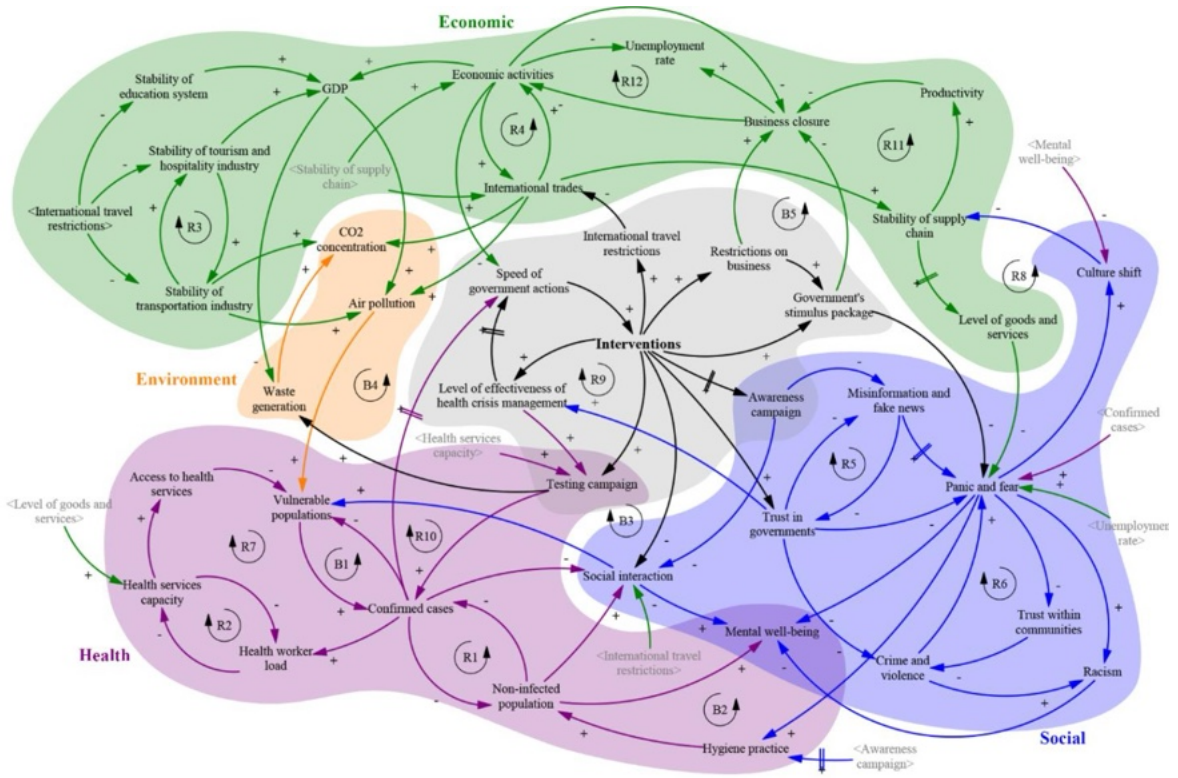
- Some challenges of application of causal loop diagrams as a systems thinking tool
- Network theory measures as a potential way to address them
- Review of network theory measures applications to CLD analysis from the literature
- Using network theory measures in an empirical study comparing the healthcare systems of Tanzania and Zambia

CLDs as a systems thinking tool

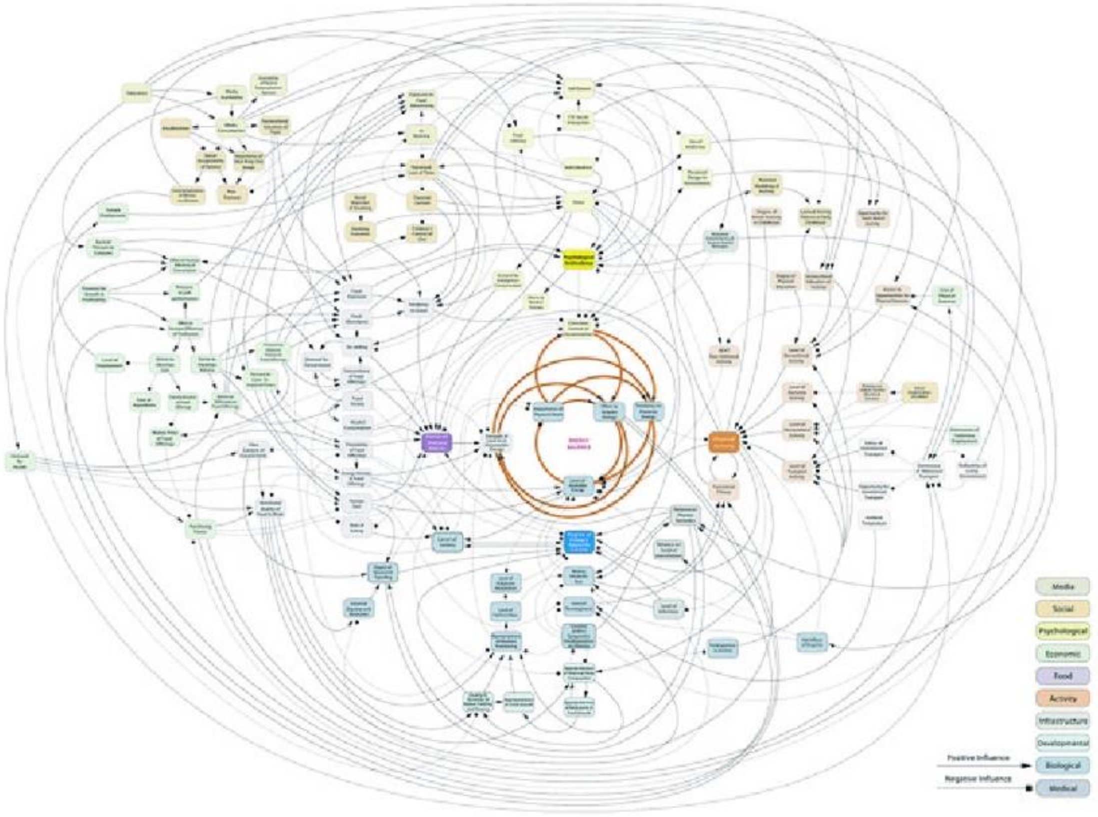
- Causal Loop Diagrams (CLDs) visualise interdependencies within systems
- CLDs illustrate the **complexity** and **interconnectedness** of the system, revealing how changes in one element affect others
- CLDs enhance comprehension of dynamic behaviour by highlighting indirect effects and feedback loops
- CLDs serve as a communication tool, facilitating discussions among stakeholders
- Using CLDs fosters a shared understanding, aligning diverse perspectives for collective action



Source: Sahin, O.; Salim, H.; Suprun, E.; Richards, R.; MacAskill, S.; Heilgeist, S.; Rutherford, S.; Stewart, R.A.; Beal, C.D, 2020. Developing a Preliminary Causal Loop Diagram for Understanding the Wicked Complexity of the COVID-19 Pandemic. *Systems*, 8, 20.

Challenges of CLD application

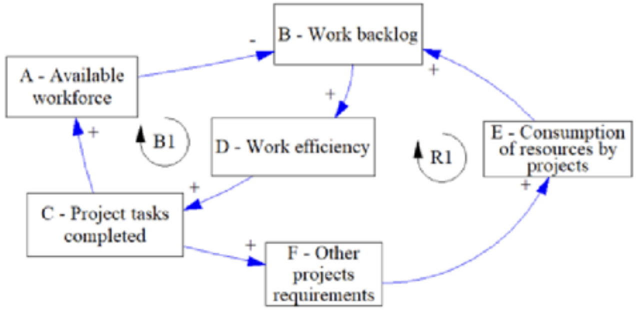
- **Managing complexity**: Large, interconnected systems can make CLDs difficult to comprehend
- **Bias and subjectivity**: Personal bias can influence how variables and relationships in CLDs are interpreted



Source: Produced by ShiftN for Government Office for Science (2007)

Network measures for CLD analysis

- A CLD can be naturally represented as a **signed directed network** (signed digraph)
- A CLD can be formally converted to an adjacency matrix
- Network theory offers frameworks for analysing the structure and complexity of CLDs and their components

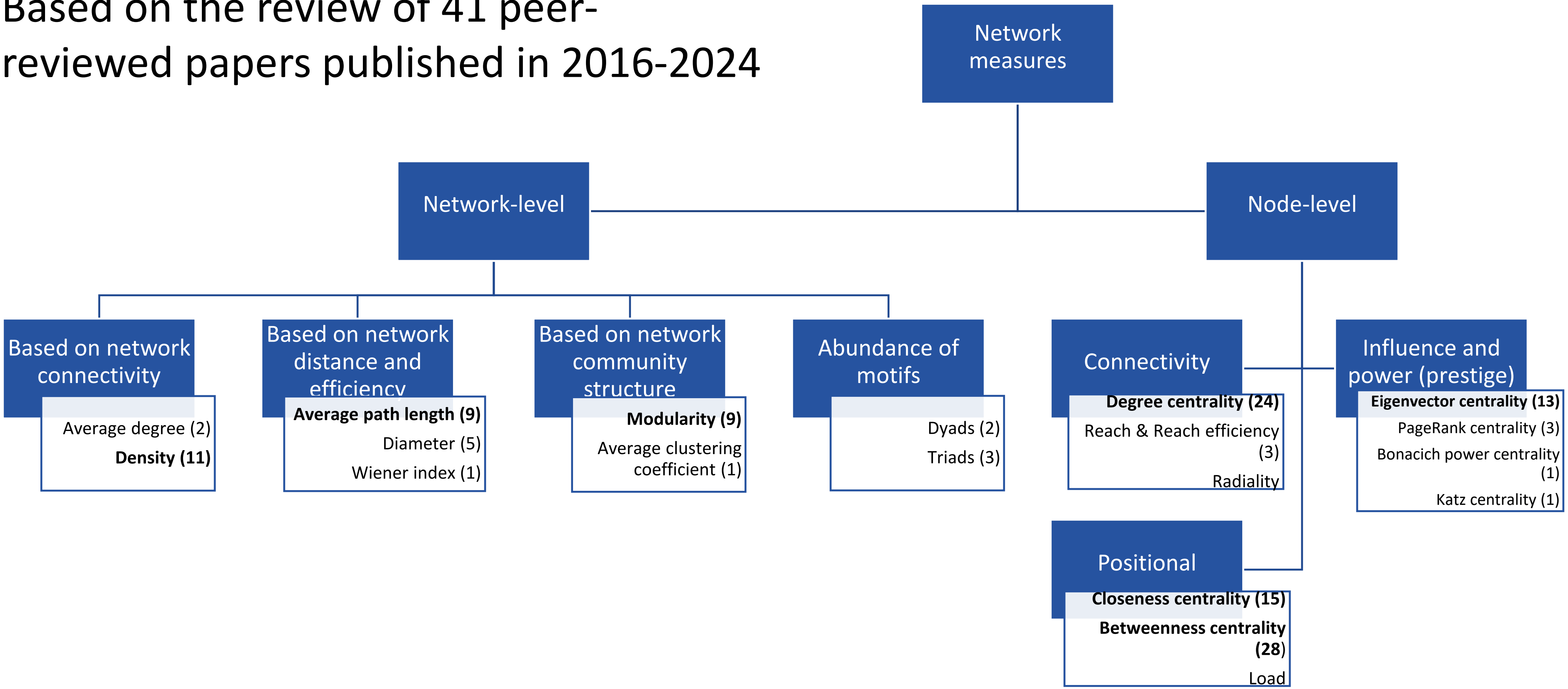


	A	B	C	D	E	F
A		-1				
B				1		
C	1					1
D			1			
E		1				
F					1	

Source: Bureš, V. (2021). *Causal Loop Diagrams and Automated Identification of Feedbacks in Economic Systems* (J. Maci, P. Maresova, K. Firlej, & I. Soukal, Eds.; International scientific conference Hradec Economic Days, 25 – 26 March 2021, pp. 123–133).

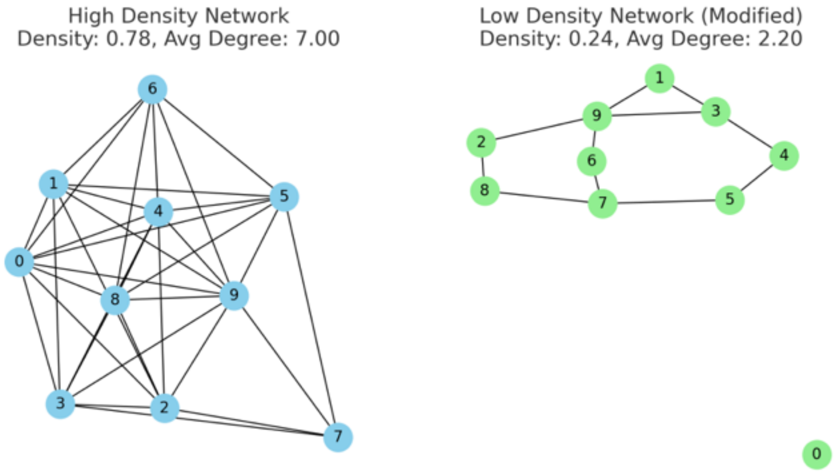
Network measures for CLD analysis - review

Based on the review of 41 peer-reviewed papers published in 2016-2024



Network-level – connectivity

- **Average degree (AD)**
    - Measures the average number of edges per node
    - A higher AD indicates greater interconnectedness among components
    - In a system with a high AD, changes in one part of the system can more readily influence others
- **Density**
    - Ratio of actual edges relative to the maximum possible edges for the given number of nodes
    - Higher density indicates a tightly connected network, likely to exhibit systemic responses to changes
    - A high density can complicate the analysis and development of intervention strategies

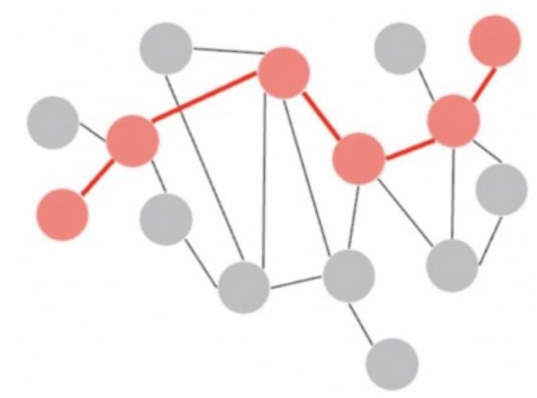


Source: Authors' own elaboration

Network-level – distance and efficiency

- **Average path length (APL)**
  - Measures the mean number of edges between all pairs of nodes in a CLD
  - A shorter APL indicates a more interconnected network, facilitating efficient impact propagation
- **Diameter**
  - Indicates the longest of shortest paths between any two nodes
  - A smaller diameter suggests that influences can spread more rapidly across the system
- **Wiener index**
  - Quantifies the compactness of a network by summing the shortest path lengths
  - A lower Wiener index reflects a more efficient structure for disseminating information and implementing interventions.

Shortest path



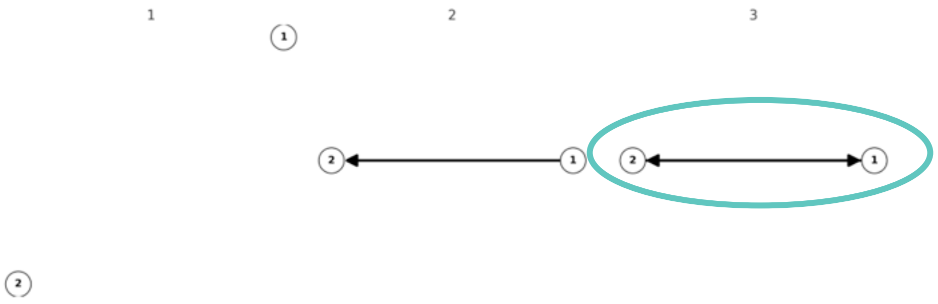
Source: Tanglay, O.; Dadario, N.B.; Chong, E.H.N.; Tang, S.J.; Young, I.M.; Sughrue, M.E. Graph Theory Measures and Their Application to Neurosurgical Eloquence. *Cancers* **2023**, *15*, 556.

Network-level – community structure

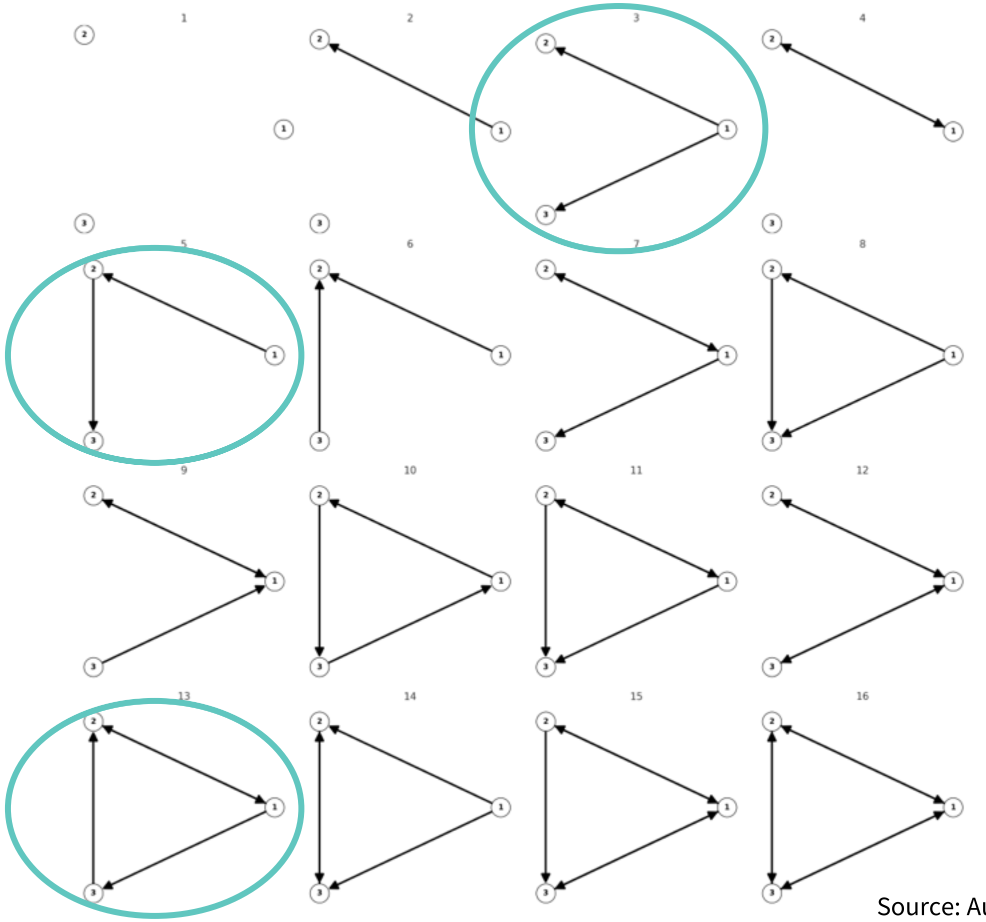
- **Modularity**
  - Measures the strength of division of a CLD into clusters
  - High CLD modularity indicates dense interconnections within clusters
  - Identifying clusters aids in targeting interventions effectively
- **Average clustering coefficient (ACC)**
  - Reflects the degree to which nodes cluster together
  - A high ACC suggests strong local connectivity
  - Helps in recognizing tightly-knit communities that can influence system behaviour

Network-level – motifs (dyads and triads)

- **Motifs** are the simplest hierarchical network structures that constitute the building blocks
- The dynamical behaviour of a system can be explicitly defined by the number and type of triads (Honti et al., 2019)
- Some studies argue that the prevalence of certain motifs in CLDs (mental models) indicates systems thinking (Aminpour et al., 2021)



Dyads

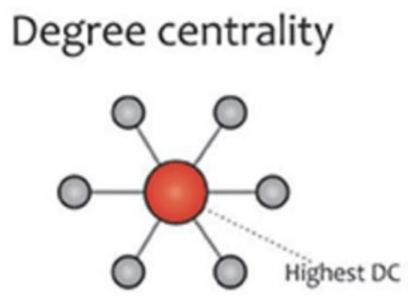


Triads

Source: Authors' own elaboration

Node-level – connectivity

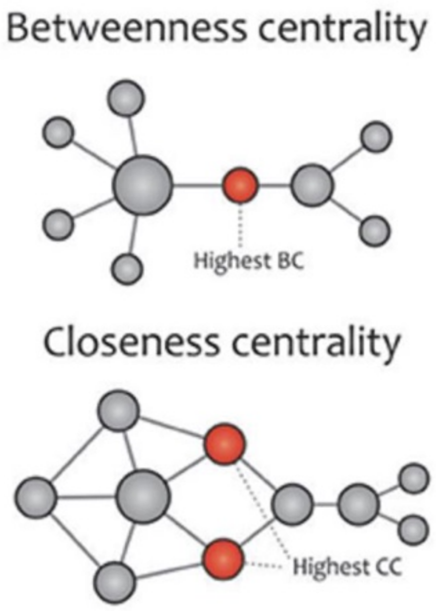
- **Degree centrality (DC)** is the total number of direct edges a node has in a CLD
    - **In-degree** is the total number of incoming edges and characterises a node's impact on the system
    - **Out-degree** is the total number of outgoing edges and characterises dependence on other nodes
    - **High-DC nodes** often act as hubs / emitters / receivers
- **Reach** measures how many nodes can be accessed from a given node within a certain number of steps, highlighting its potential to spread influence throughout the network
- **Reach efficiency** reflects how efficiently a node connects to a large portion of the network without redundancy, emphasising its ability to influence the system with minimal direct edges



Source: Farahani, F.V.; Karwowski, W.; Lighthall, N.R. Application of Graph Theory for Identifying Connectivity Patterns in Human Brain Networks: A Systematic Review. *Front. Neurosci.* 2019, *13*, 585.

Node-level – position

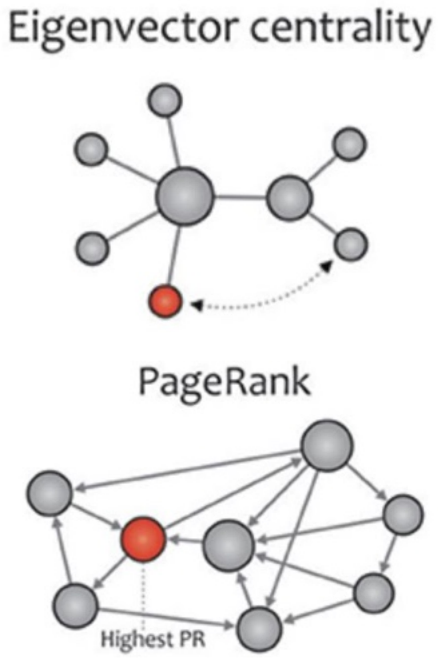
- **Betweenness centrality (BC)** measures how often a node acts as a bridge along the shortest path between two other nodes
    - High-BC nodes may be key connectors that control information flow
- **Closeness centrality (CC)** assesses how close a node is to all other nodes
    - Nodes with high CC can influence others quickly, making them potential leverage points for interventions



Source: Farahani, F.V.; Karwowski, W.; Lighthall, N.R. Application of Graph Theory for Identifying Connectivity Patterns in Human Brain Networks: A Systematic Review. *Front. Neurosci.* 2019, *13*, 585.

Node-level – influence and power (prestige)

- **Eigenvector centrality (EC)** measures a node's importance by considering its connections to other influential nodes, giving insight into the influence of a node within the system
    - **High-EC nodes** are influential and well-connected variables, making them potentially effective targets for driving system-wide changes and understanding feedback loops
- **Katz centrality (KC)** adds some value for each node by default but penalises remote connections => more useful for directed networks
- **PageRank centrality (PR)** normalises by Katz centrality, dividing it by the out-degree of the node



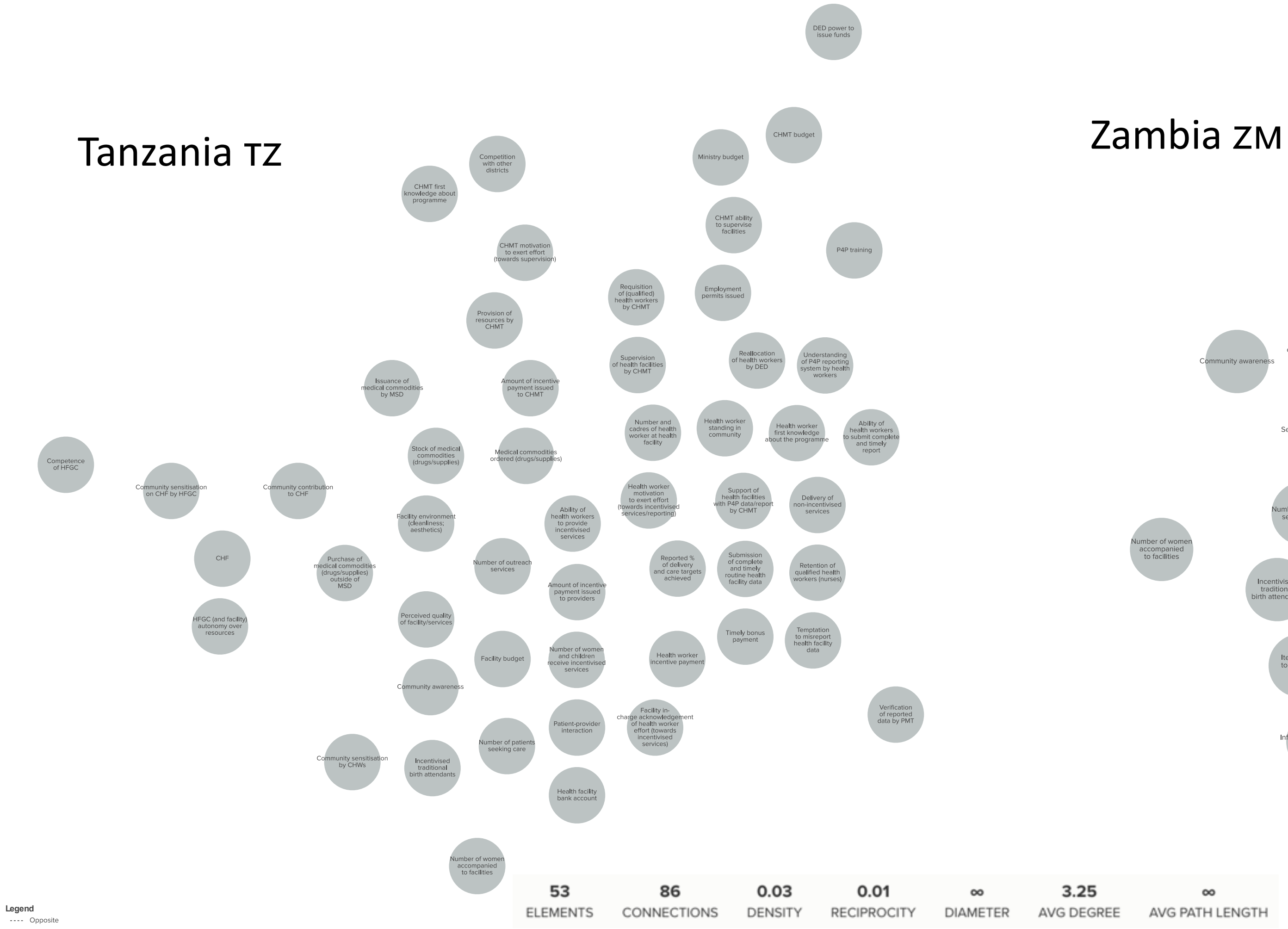
Source: Farahani, F.V.; Karwowski, W.; Lighthall, N.R. Application of Graph Theory for Identifying Connectivity Patterns in Human Brain Networks: A Systematic Review. *Front. Neurosci.* 2019, *13*, 585.

Case-study: maternal and child health system response to payment for performance in Tanzania and Zambia

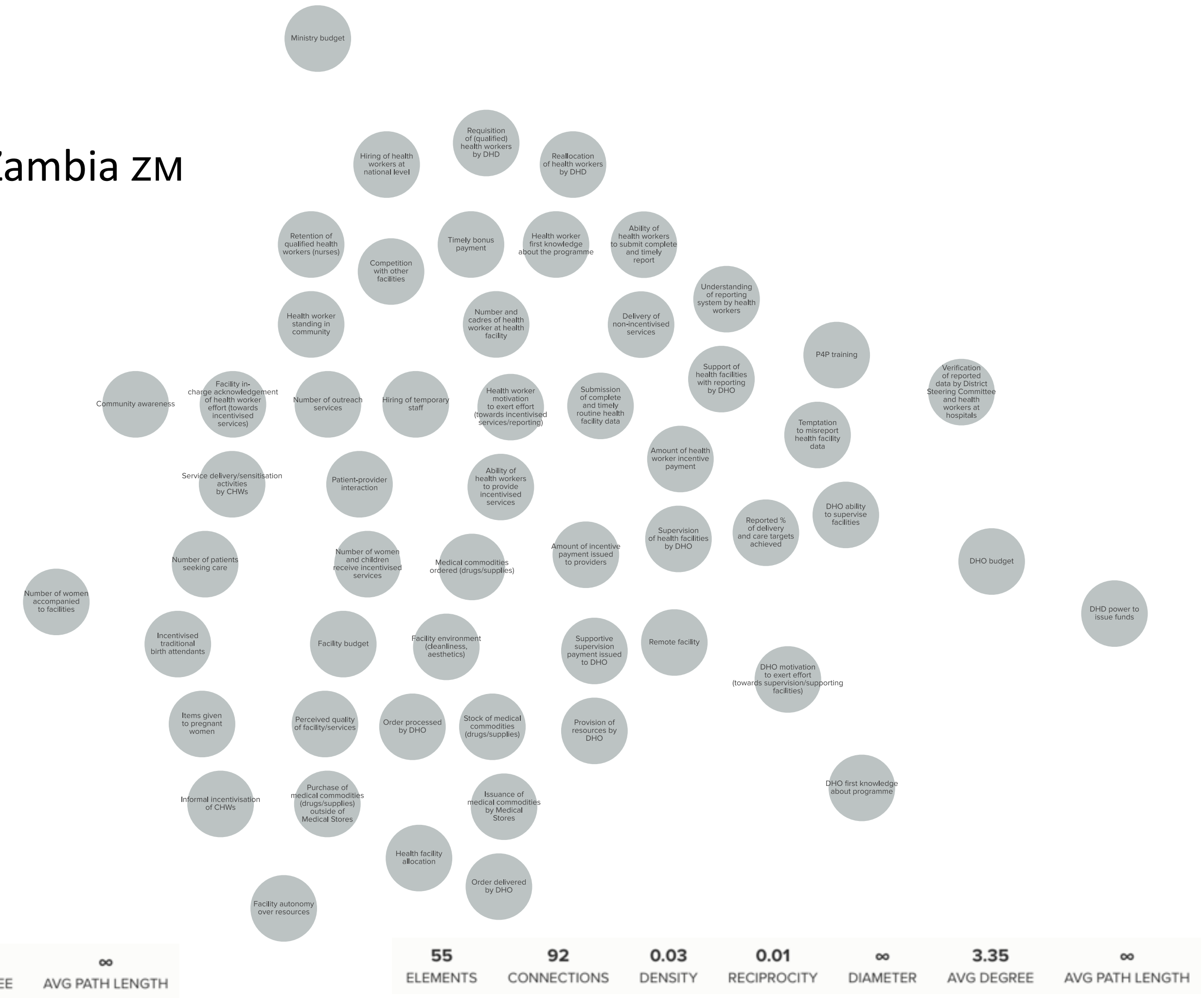
- CLDs were developed to explore the effects of **payment for performance (P4P)** schemes in **Tanzania** and **Zambia**
- This involved assessing **health worker incentives** and their impact on **maternal and child health systems**
- The CLDs were validated using qualitative data from process evaluations and **stakeholder dialogues**
- The study identified key health system mechanisms affected by P4P, focusing on the **number of women and children receiving incentivised services**
- Variations across the two countries were explored, shedding light on how differences influence P4P mechanisms and outcomes

CLDs for Tanzanian and Zambian MCH systems

Tanzania TZ



Zambia ZM



Source: Authors' own elaboration

Network measures applied to CLD for Tanzania

- Using multi-measure approach

Label	outdegree	indegree	degree	betweenness	closeness	eigenvector	reach	reach-efficiency
Health worker motivation to exert effort (towards incentivised services/reporting)	**7**	**8**	**15**	0,28097	0,33117	0,04956	0,27273	0,01705
Number and cadres of health worker at health facility	**7**	4	11	0,16055	0,30141	0,02317	0,23636	0,02149
Stock of medical commodities (drugs/supplies)	5	4	9	0,18578	0,28549	0,05348	0,21818	0,02182
Facility budget	**7**	1	8	0,19193	**0,33364**	0,02366	**0,29091**	0,03232
Number of women and children receive incentivised services	3	5	8	0,27314	0,28364	**0,07776**	0,21818	0,02424
Amount of incentive payment issued to providers	3	4	7	**0,30914**	0,29753	0,05196	0,25455	0,03182
Ability of health workers to provide incentivised services	2	3	5	0,13499	0,26358	0,03981	0,21818	0,03636
Number of outreach services	2	3	5	0,04857	0,23011	0,04389	0,12727	0,02121
Perceived quality of facility/services	1	4	5	0,03686	0,17299	0,04444	0,05455	0,00909
Purchase of medical commodities (drugs/supplies) outside of Medical Stores	1	4	5	0,05136	0,20472	0,02629	0,12727	0,02121
Supervision of health facilities by DHO	3	2	5	0,12101	0,28364	0,00996	0,25455	0,04242
Ability of health workers to submit complete and timely report	1	3	4	0,03989	0,17983	0,01742	0,05455	0,01091
Issuance of medical commodities by Medical Stores	3	1	4	0,05359	0,1996	0,00973	0,09091	0,01818
Number of patients seeking care	1	3	4	0,08281	0,21067	0,03259	0,09091	0,01818
Temptation to misreport health facility data	1	3	4	0,04008	0,17828	0,01284	0,05455	0,01091
Amount of health worker incentive payment	2	1	3	0,0559	0,24956	0,02366	0,2	0,05

Source: Authors' own elaboration

Policy implications

- Key nodes in Tanzania and Zambia include **health worker motivation**, **drug stock**, and **supervision by districts**.
- Potential leverage points: **staffing levels at facilities** is common leverage points in both countries.
- Differences between countries
    - Zambia's **facility budget** is a stronger leverage point due to its higher share of the funds and greater autonomy in fund usage, including hiring retired midwives. This might explain better outcomes in deliveries
    - In Tanzania, the **CHF** (community insurance scheme) enhances facility budgets, and a similar approach to national health insurance could be applied in Zambia.
- **Financing reforms** are critical for performance improvement. Proper funding is the key to enabling **staffing** and **drug availability**, which in turn play a vital role in motivating health workers and improving **service delivery**

Applications of network analysis to CLDs

- **Managing complexity**: Network theory can help structure large, complex CLDs by identifying key nodes (variables) and edges (causal links), reducing the cognitive load of interpretation
- **Bias and subjectivity**: Network theory can offer quantitative measures (e.g., node importance metrics) to complement subjective judgment, making CLD analysis more objective and data-driven
- **Identification of feedback loops and causal pathways**: Network theory can help identify critical paths and feedback loops, allowing for better focus on the key areas
- **Validation**: Network theory can help identify the most influential variables and validate causal relationships

Limitations of network analysis of CLDs

- Network metrics might oversimplify the complexity of CLDs, potentially overlooking nuanced relationships (links polarity!) and feedback loops that are critical for accurate system representation
- Currently applied network measures may not adequately capture the dynamic nature of systems as well as delays
- Standardised metrics and frameworks are needed to enhance comparability across studies, which would facilitate the synthesis of findings and the broader applicability of insights

Future research directions

- Application of centrality measures more specific to CLD representation, i.e., those developed for the analysis of **signed directed** networks
- Validation of network analysis insights by stakeholders participating in CLD development
- Exploring opportunities for cross-disciplinary collaboration combining insights from network theory, system dynamics, and systems thinking
- Development of user-friendly software tools that integrate advanced network measures will empower non-experts to use CLDs effectively, promoting broader application in diverse fields
- Compare CLDs across different contexts by systematically applying network measures,
- Identification of critical elements for simulation models

Preliminary conclusions

- Integrating network measures into CLD analysis can bridge the gap between qualitative and quantitative analysis
- It enhances the identification and interpretability of complex relationships and feedback mechanisms within systems
- By leveraging network analysis, complex CLDs can be made more accessible, insightful, and actionable for decision-makers, ultimately contributing to a better understanding and management of complex systems

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Thank you.

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