

Network Analytic Approaches for HSRB DAG Development

Erik Antonsen MD, PhD, Robert Reynolds, PhD, Kevin H. Hyuhn, John Arrellano,
PhD, Ahmed Abukmail, PhD, Mary Van Baalen, PhD

NASA Investigators Workshop, Galveston, TX - February 14, 2023

Information and Complexity

- ❖ “The Columbia Accident Investigation Board (CAIB) report attributed some causality to what they termed “dysfunctional databases” [Columbia Accident Investigation Board 2003]. The CAIB found that there were about *50 separate PRACA systems for shuttle, each with its own nomenclature and processflow*. It was not possible to see patterns across the PRACA systems. To this day, there are hundreds of processes and engineering data analysis repositories for other data, such as Hazards Analyses and Failure Modes Effects Analyses, and for each type of data, there are many independent repositories. **People misattribute accidents to unknown unknowns, but, if one examines the history of such events across complex engineered systems, it becomes clear that the source is most often unknown knowns: the information is in our data systems, but we simply cannot see the relationships.**”

Johari Window

	Known	Unknown
Known	<p><i>Known Knowns</i></p> <p>Things we are aware of and understand</p>	<p><i>Known Unknowns</i></p> <p>Things we are aware of but don't understand</p>
Unknown	<p><i>Unknown Knowns</i></p> <p>Things we understand but are not aware of</p>	<p><i>Unknown Unknowns</i></p> <p>Things we are neither aware of nor understand</p>

Category	Failure Modes	Solution Space
Known Knowns	Conceptual Failures Failures of Prioritization Failures of Systems Engineering	Risk Analysis Prioritization Principles Human Systems Integration
Known Unknowns	Failures in research Failure of prioritization	Human Research Programs Space Biology
Unknown Knowns	Inability to query complex systems	?
Unknown Unknowns	Failures of Imagination	?

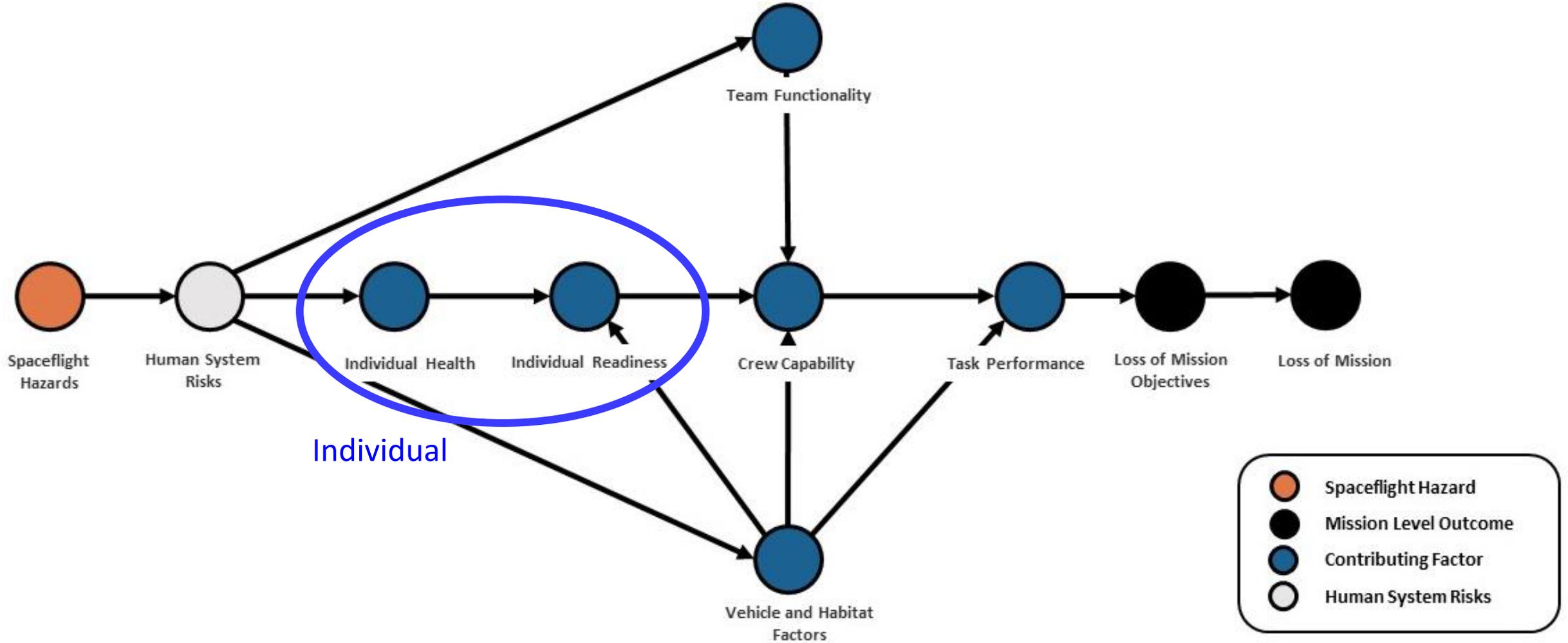
NASA HSRB
Current July 2023

What can we actually quantify?

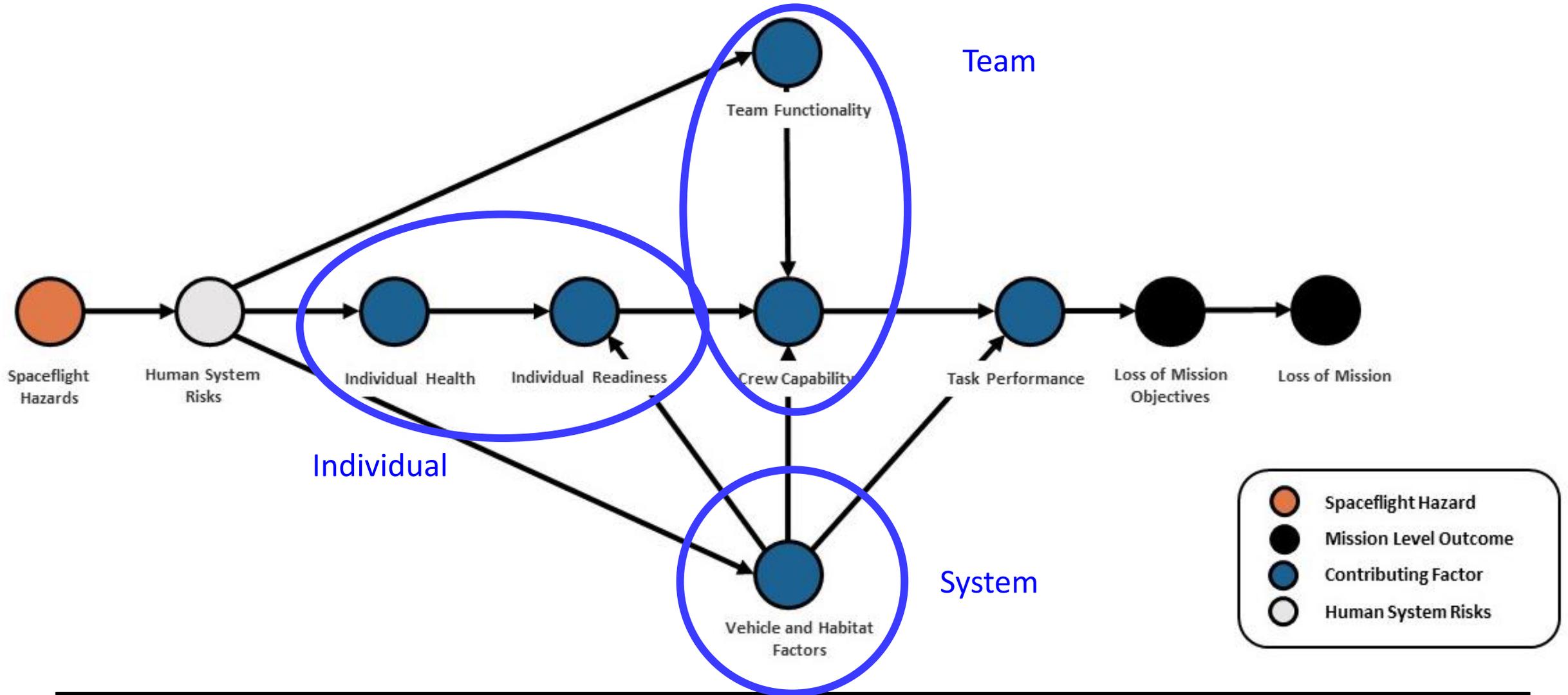
Silo

Human System Risk/Concern	Design Reference Mission							
	Low Earth Orbit		Lunar Orbital		Lunar Orbital +		Mars	
	< 30 D	30 D - 1 Y	< 30 D	30 D - 1 Y	< 30 D	30 D - 1 Y	< 1 Y	730 - 1224 D
	In Mission Risk - Operations							
Aerobic Capacity Risk	Green	Green	Green	Green	Yellow	Yellow	Yellow	Yellow
Behavioral Medical Risk	Green	Yellow	Green	Yellow	Yellow	Yellow	Red	Red
Bone Fracture Risk	Green	Green	Green	Green	Yellow	Yellow	Green	Red
Cardiovascular Risk	Green	Green	Green	Green	Yellow	Yellow	Green	Red
Celestial Dust Risk	Grey	Grey	Green	Green	Green	Yellow	Grey	Red
CO2 Risk	Yellow	Yellow	Green	Green	Green	Green	Yellow	Yellow
Crew Egress Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Decompression Sickness Risk	Green	Green	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Dynamic Loads Risk	Yellow	Yellow	Yellow	Yellow	Red	Red	Yellow	Red
Electrical Shock Risk	Green	Green	Green	Green	Yellow	Yellow	Yellow	Yellow
EVA Injury Risk	Yellow	Yellow	Yellow	Yellow	Red	Red	Yellow	Red
Food and Nutrition* Risk	Green	Green	Green	Green	Yellow	Yellow	Red	Red
Hearing Loss Risk	Green	Green	Green	Green	Green	Yellow	Yellow	Yellow
Human System Integration Architecture Risk	Yellow	Yellow	Yellow	Yellow	Red	Red	Red	Red
Hypoxia Risk	Green	Green	Green	Green	Green	Yellow	Yellow	Yellow
Immune Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Ineffective or Toxic Medication (Pharmaceutical) Risk	Green	Green	Green	Green	Green	Yellow	Yellow	Red
Medical Conditions Risk	Green	Yellow	Yellow	Red	Yellow	Red	Red	Red
Microhost Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Muscle Size, Strength and Performance Risk	Green	Green	Green	Green	Yellow	Yellow	Yellow	Yellow
Non-Ionizing Radiation Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Renal Stone Risk	Green	Yellow	Green	Yellow	Green	Yellow	Yellow	Red
Sensorimotor Risk	Green	Green	Green	Green	Red	Red	Green	Yellow
Sleep Loss Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Team Risk	Yellow	Yellow	Yellow	Yellow	Red	Yellow	Red	Red
Toxic Exposure Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Urinary Retention Risk	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
Venous Thromboembolism (VTE) Concern	Grey	Grey	Grey	Grey	Grey	Grey	Grey	Grey
	Post Mission Risk - Long Term Health							
Carcinogenesis* Risk	Green	Yellow	Green	Yellow	Green	Yellow	Yellow	Yellow
Spaceflight Associated Neuro-ocular Syndrome Risk	Green	Green	Green	Yellow	Green	Yellow	Yellow	Red

How are health and performance related?



How are health and performance related?



Knowledge Graphs and Complexity

- ❖ **NASA's DAGs use a harmonized terminology with common definitions. This allows graphs to be adjusted to overlay one another at common nodes.**
- ❖ **By combining these graphs into a single large risk network, unanticipated linkages are created that enable us to explore the unknown known domain – areas where we have information, but historically lack the analytic capability to bring it to our awareness.**
- ❖ **Here we explore the analytics that can be used on these networks.**

Whole Network Measures

Metric	Example Measures	Comments
Whole Network Measures		
Network Size	Diameter, Radius, Average Path Length	These measures are used to gauge how quickly or efficiently signals (information, contagion, etc.) can move across a network. In the context of spaceflight risks, this can index network sizes of individual risks, giving a sense of how much opportunity for intervention there may be, on average.
Network Complexity	Network Density, Clustering Coefficient	These measures are most insightful when changes to a network are proposed, such as when selecting one countermeasure to implement from among a set of alternatives. All else being equal, the countermeasure that results in the lowest increase in network complexity (as measured by changes in the density and the clustering coefficient) would be preferred.

Node Importance Measures

Node Importance Measures

Centrality

Total Degree,
Betweenness,
Closeness,
Eigenvector,
Katz Centrality,
Page Rank

Centrality measures describe the importance of a node in terms of its structural role or location. Nodes that are high in centrality tend to be those that have many connections, tend to unite portions of the network that otherwise would be disconnected, or are related to other important nodes. Depending on the type of centrality considered, these metrics can identify nodes that are important to control for downstream risk reduction.

Subgraph Isolation and Analysis

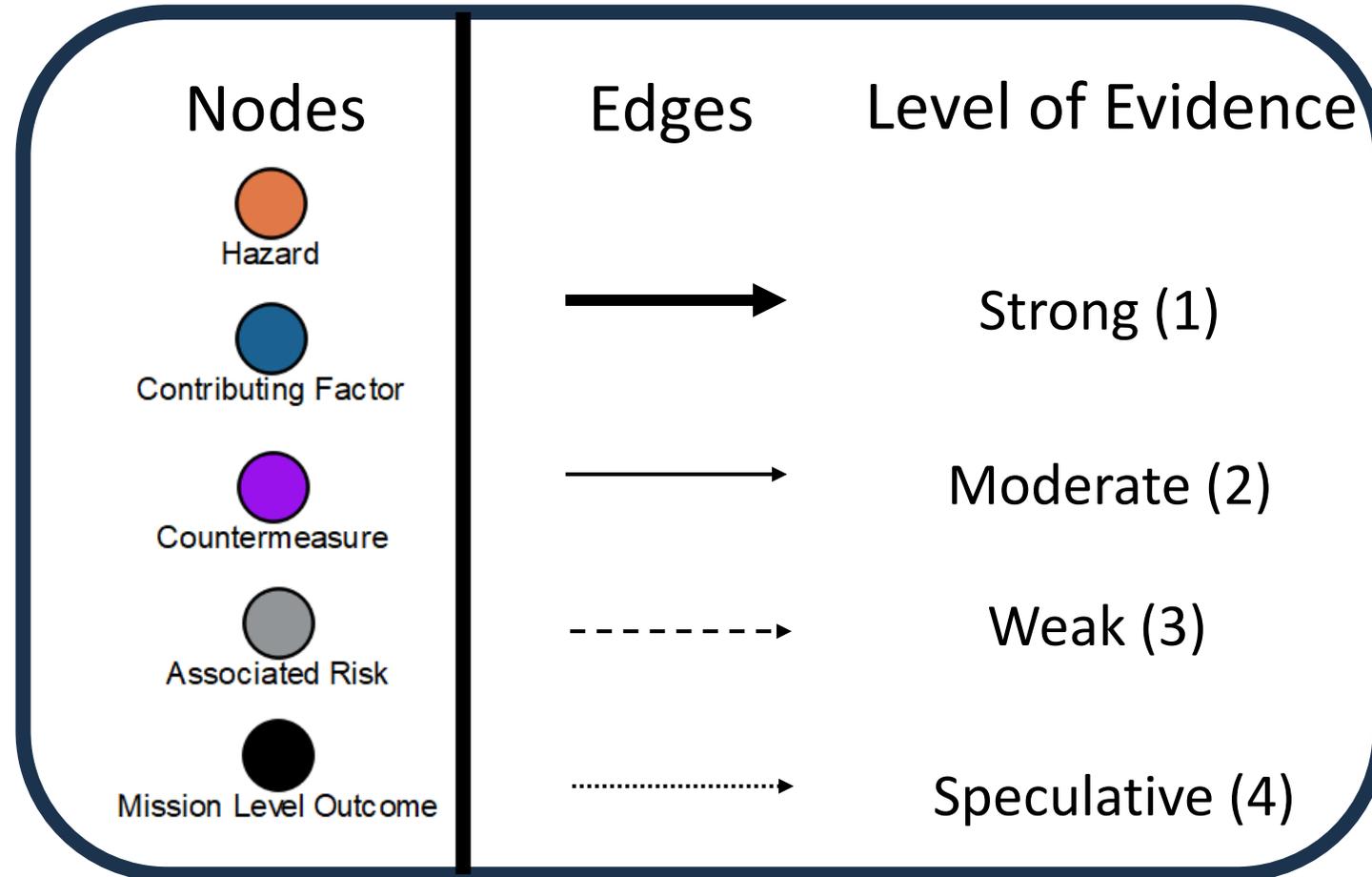
Subgraph Isolation and Analysis		
Path tracing	Adhesion, Main Path Analysis	Path tracing creates a sub-graph by capturing only the pathways that include one or more specific nodes. Typically path tracing is most useful for isolating all causal pathways that involve a particular node when evaluating that node as a mitigation target. This is particularly helpful for communicating how distant nodes are related to each other.
Ego Networks	N-step neighborhood, Directionality	An ego network is formed by isolating all nodes that are within a specified distance (the radius, r) of a starting node. The resulting graph places the starting node in the center of the network, with all its r -degree connections, as well as any of the connections those nodes have with each other. A local ego network can help identify specific strategies for developing countermeasures. Ego networks may be further limited to either incoming or outgoing edges.
Community Detection	Louvain groups, Leiden Community Detection	Community-detection methods are essentially clustering algorithms based on network distances. Applying community detection algorithms to spaceflight causal networks, particularly to the merged single-risk causal network, can expose the causes and effects that are most closely intertwined. This can provide a better understanding of the structurally defined sub-systems within the total causal system. Once communities have been identified, they can be isolated as sub-graphs, and then the other forms of analysis described here can be applied. If the results are used strategically, this can be a powerful tool for managing and coordinating scientific resources.
Graph faithfulness	Marginal Dependencies, Conditional Independencies	The structure of the DAGs and their causal interpretations define the resulting dependence and independence of the nodes in the network. The procedure of D-separation can be used to determine which nodes are marginally or conditionally independent of each other. This is useful when first drawing a DAG because these independence statements have conceptual meanings that can provide a face validity check for the network. They can also be used, in conjunction with data, to validate network structure (57).

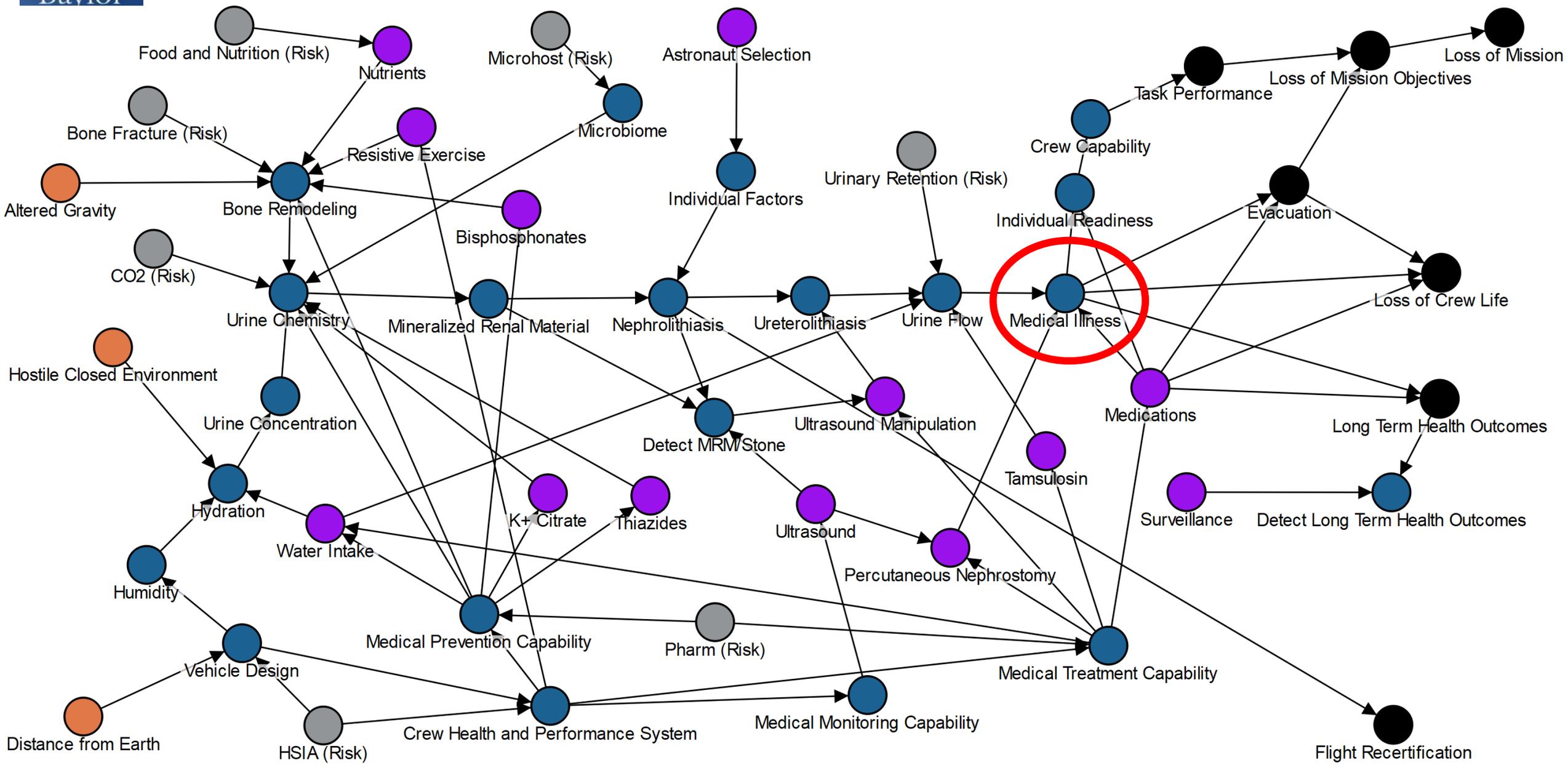
Computational Models

Computational Models

Regression	Path modeling, Structural equation modeling	Path models and structural equation modeling (SEM) are methods for fitting a regression over the structure of a DAG. The regression coefficients that these models produce quantify the amount of change expected in an effect variable, given a change in a causal variable (all else being equal) (64). These models are powerful because they can estimate causal effects for variables that were not measured. SEM is an evolved version of path modelling that enables more sophisticated assumptions to be made about the relationships between variables (64,65). Path models and SEM can be used to elucidate the strongest influences on a multi-causal effect, the downstream effect of changes in a particular factor, etc.
Bayesian networks	Probabilistic Reasoning	Bayesian networks (BNs) are causal DAGs that include joint probability distributions (52). Functionally, this means each node includes a probability distribution that depends on the values assumed by its causes. The best use for BNs in managing spaceflight-induced human system risks is to compute the change in probability of a particular outcome after either editing the network structure (interventions) or changing the evidence (such as assuming a different mission design).

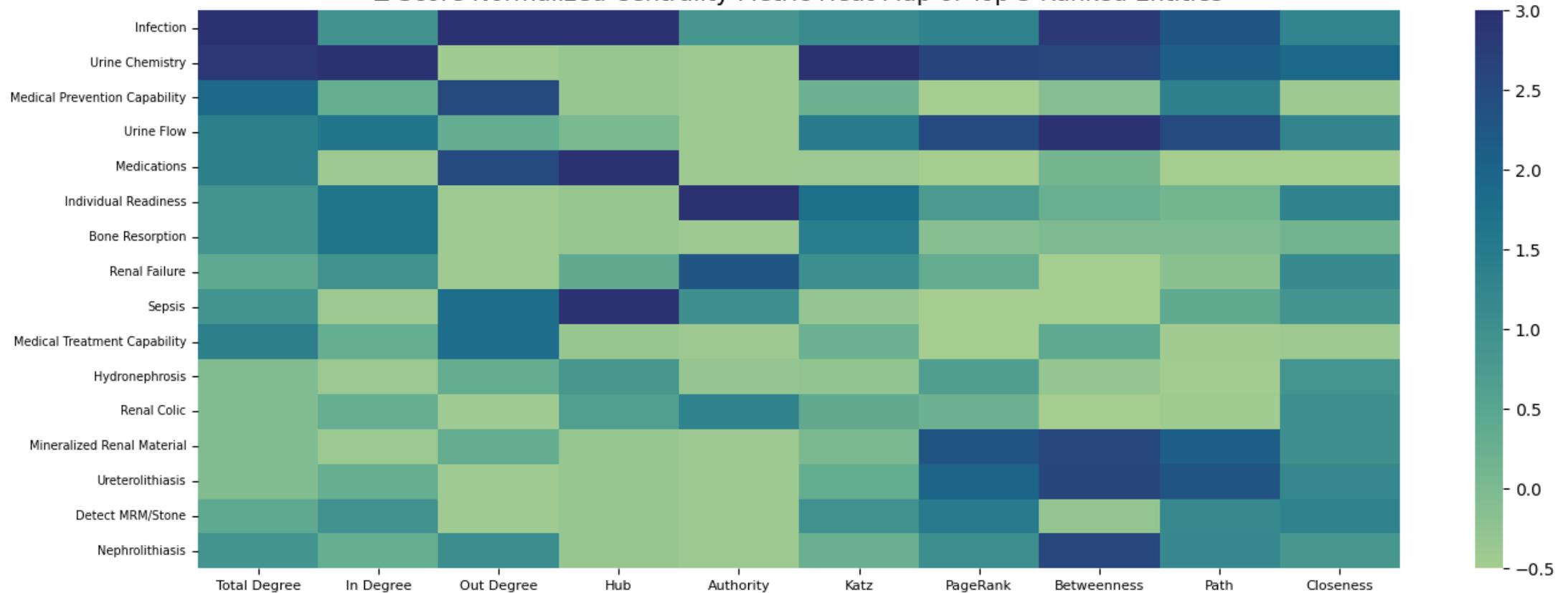
Legend





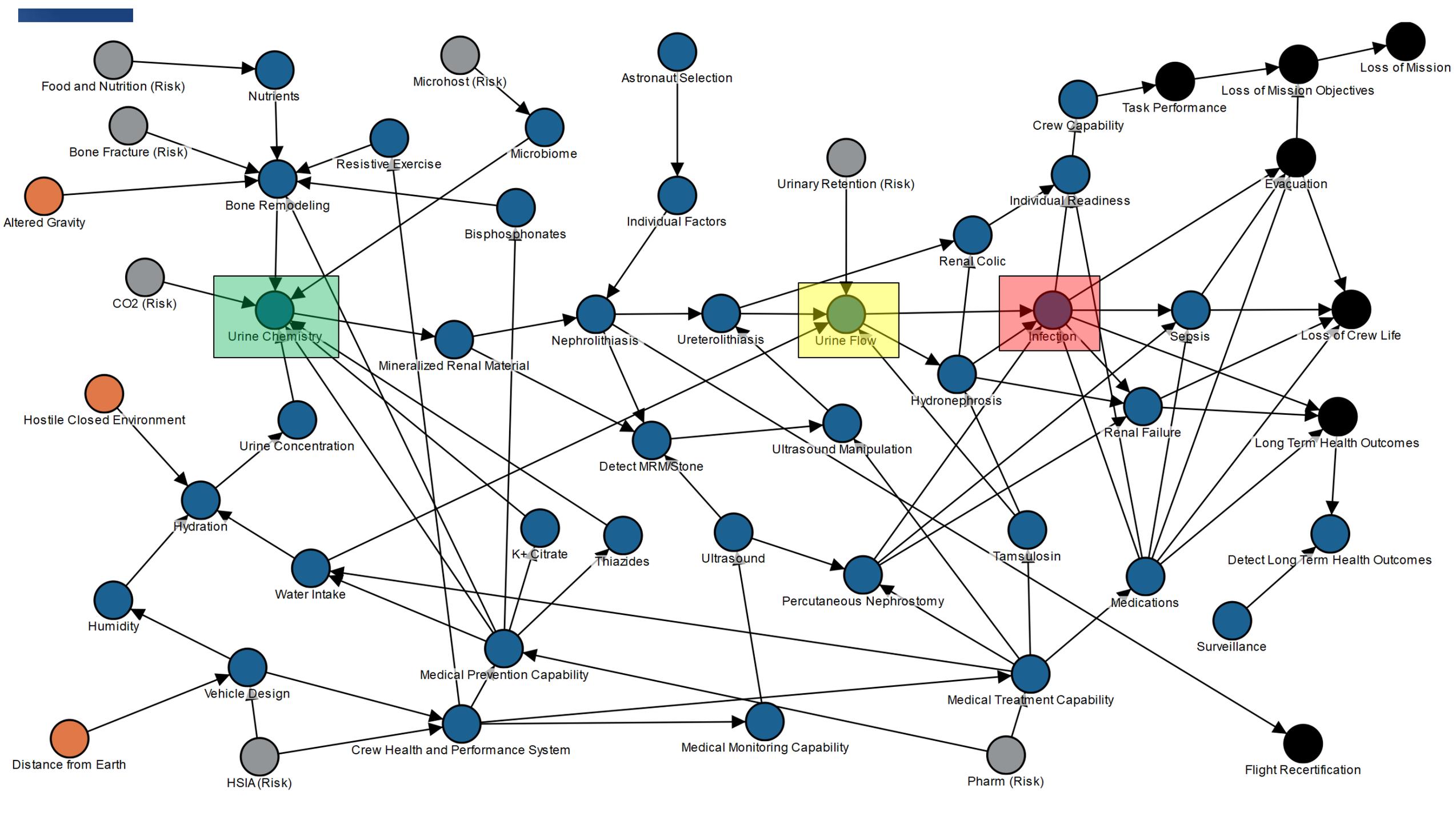
Centrality Analysis of the Renal Stone DAG

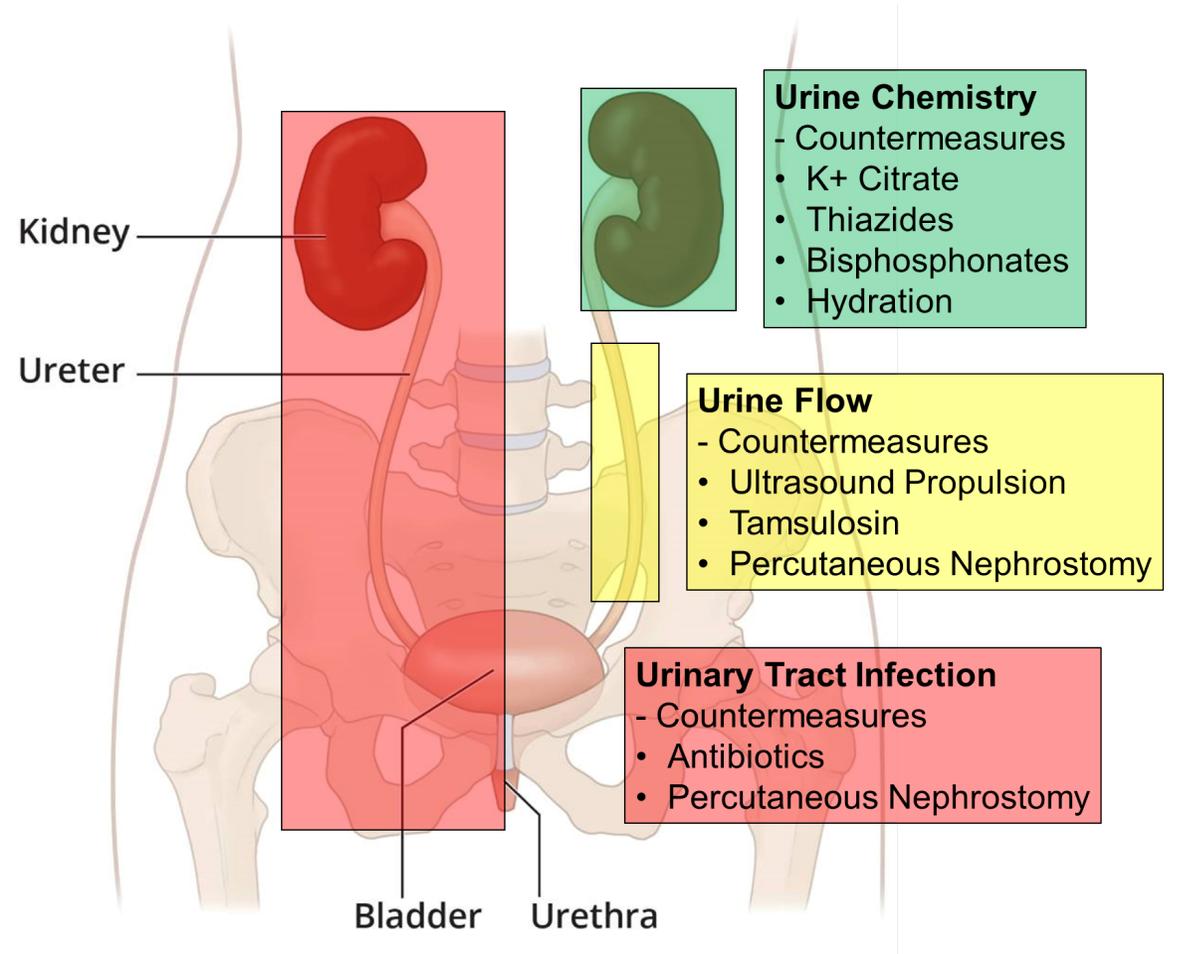
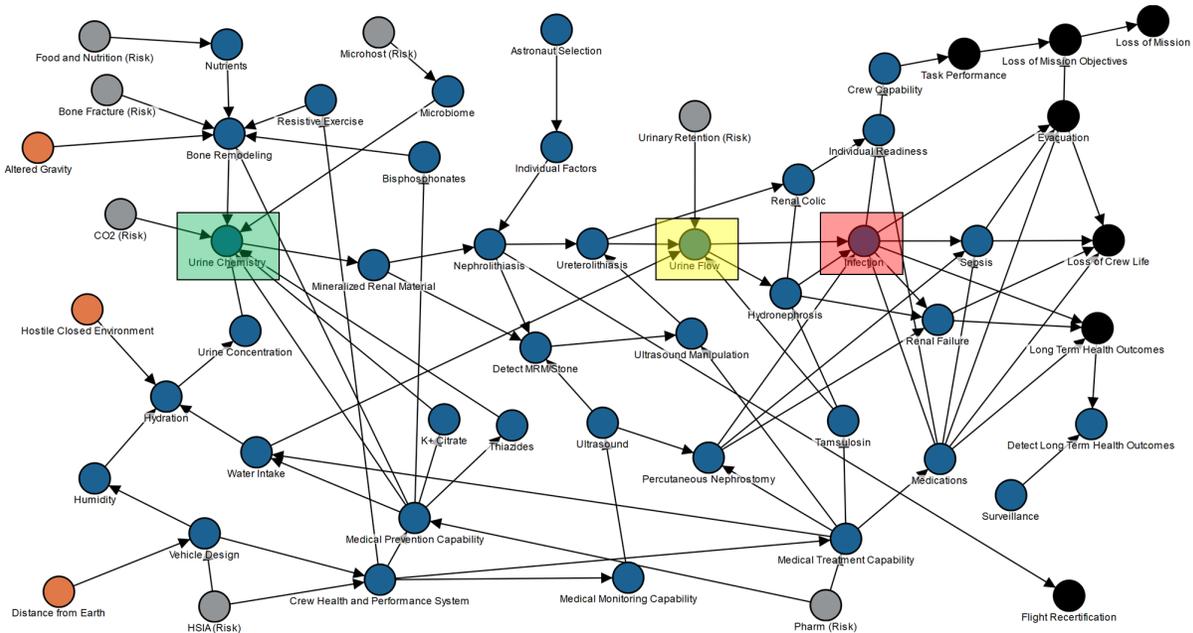
Z-Score Normalized Centrality Metric Heat Map of Top 5 Ranked Entities



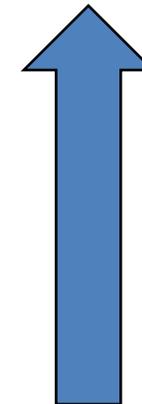
Highest aggregate centrality corresponds to anatomy

Number of Times Ranked Top Five	Entities
8	Infection
7	Urine Flow
6	Urine Chemistry
4	Individual Readiness
3	Sepsis, Ureterolithiasis, Mineralized Renal Material, Medications





Category	Failure Modes	Solution Space
Known Knowns	Conceptual Failures Failures of prioritization Failures of Systems Engineering	Improved Risk Analysis Risk Management Prioritization Human Systems Integration
Known Unknowns	Failures in research Failure of prioritization	Research Programs Risk Management
Unknown Knowns	Inability to query complex systems	<i>Systems Medicine</i> <i>Causal Diagramming</i> <i>Network Analysis</i> <i>AI/ML</i>
Unknown Unknowns	Failures of Imagination	<i>System Margin (Resilience)</i>



Goal: Change unknowns into knowns

Conclusions

- ❖ Knowledge graph and network analysis present opportunities to engage with cross-risk complexity in a new way.
- ❖ This depends on the creation of data systems and the successful curation and integration of data that spans longitudinal environmental and human states in spaceflight.
- ❖ Initial analyses of centrality measures for the DAGs have been consistent with face value expectations. This is similar to initial structural validation approaches using data.
- ❖ Causal diagramming, network analysis, systems medicine, and AI/ML have the potential to move problems from the unknown known category into known knowns that can be quantified, prioritized, and addressed.

Backup Slides

