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Abstract Title:
A method for validating causal diagrams of human health risk in space flight

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Abstract:

The complexity of cause-and-effect relationships between spaceflight hazards and resulting health conditions clouds understanding of the totality of human system risk in space. In response, NASA has introduced Directed Acyclic Graphs (causal diagrams) into the human systems risk management process. These diagrams allow for a common understanding of the mechanisms that lead from unique hazards of spaceflight to the health outcomes important to agencies and astronauts. However, the paucity of available biomedical data from spaceflight creates a need for methods of validating causal models that can accommodate data from spaceflight model analogs. Here we outline one approach utilizing open-access rodent bone datasets from the Ames Life Sciences Data Archive. The properties of directed acyclic graphs themselves can provide an epistemological and statistical framework for validation of a priori causal representations of human system risk in space flight. The assumed causal connections on the graph creates sets of logical implications: variables that – if the causal diagram is correct – should be correlated, as well as sets that should be conditionally independent. By testing these implied correlations and conditional independencies both statistically and heuristically, we can provide evidence for or against specific causal pathways on the causal diagram. In addition to validation of expert-generated causal diagrams, machine learning techniques can learn the most likely structure of a causal diagram from a given dataset. Comparison with and reconciliation between machine-learned causal diagrams and expert-generated diagrams is another technique for challenging assumptions and improving our understanding of causal mechanisms.

Accurately representing complex causation is essential to systemic understanding of human health risks in space travel. Having a robust system of validating causal diagrams helps us arrive at more accurate representations of causal systems. This process will be integral to developing the countermeasures necessary for extended exploration of the moon and Mars.

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